# Automating Elevators*

APEP Autonomous Research† @SocialCatalystLab

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**Abstract**

The automatic push-button elevator was commercially available by 1900. The occupation it replaced did not disappear until the 1970s. Combining full-count census microdata (1900–1950), published aggregates (1960–1980), a linked panel of 38,562 operators, and 20 million digitized newspaper pages, we assemble a comprehensive lifecycle of an occupation eliminated by a single technology. The newspaper record documents how discourse shifted from treating operators as trusted guides to questioning whether their jobs should exist—a transition visible in the data before the occupation's quantitative collapse. Displacement was demographically stratified: white operators moved into clerical and skilled positions while Black operators were channeled into janitorial and domestic service. New York City, where unions and building codes were strongest, exhibited markedly higher operator persistence than other cities. The forty-year gap between technological feasibility and occupational extinction is consistent with automation being mediated by social and institutional forces, not determined by technology alone.

**JEL Codes:** J23, J62, N32, O33

**Keywords:** automation, occupational transitions, elevator operators, technology adoption, labor displacement, racial inequality, newspaper discourse

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## 1. Introduction

Between 1900 and 1950, the number of Americans employed as elevator operators rose tenfold—from 7,943 to 85,294. The technology that would replace them, the automatic push-button elevator, had been commercially available since the beginning of that period. By 1980, fewer than 7,400 remained. An entire occupation had grown, plateaued, and gone extinct in the span of a single lifetime, even as the technology for its elimination existed throughout.

This paper assembles a comprehensive lifecycle of an occupation eliminated by automation and asks what it reveals about the process by which technologies displace workers. The elevator operator is an ideal case: the replacement technology was singular and identifiable (the automatic elevator), the occupation was large enough to appear in census microdata across eight decades, and the displacement happened recently enough that individual workers can be tracked through linked census records. Unlike contemporary automation anxieties, where the technologies, timelines, and affected occupations are uncertain, the elevator operator's story has a beginning, middle, and end.

We make three contributions. First, we document the arc of the occupation from 1900 to 1980, showing that the standard narrative of swift technological displacement is wrong. The occupation grew alongside its replacement technology for forty years—from 2.9 per 10,000 employed in 1900 to a rate peak of 15.6 in 1940 (absolute count peaked at 85,294 in 1950)—before beginning a gradual decline that only became collapse in the 1960s and 1970s (Figure 4). This long coexistence demands explanation, and the answer lies not in technology but in institutions, economics, and culture.

Second, we analyze the newspaper record. Drawing on the American Stories corpus of 20 million digitized newspaper pages (Dell et al., 2023), we track how public discourse about elevator operators evolved across the first six decades of the twentieth century. The narrative arc is striking: early coverage treated operators as trusted figures in urban life—part servant, part guide, part security guard—while later coverage increasingly framed them as anachronisms whose jobs could and should be automated. This discursive shift is visible in the data before the occupation's quantitative collapse in the 1960s, consistent with the hypothesis that cultural legitimacy erodes before an occupation disappears—though the sparse temporal sampling prevents precise sequencing claims.

Third, using linked census records from the IPUMS Multigenerational Longitudinal Panel (Ruggles et al., 2024), we track 38,562 individuals who worked as elevator operators in 1940 through to their 1950 occupations. Eighty-four percent exited within the decade, but their destinations were sharply unequal. White operators moved disproportionately into clerical, sales, and skilled trade positions. Black operators were channeled into janitorial work, porter positions, and domestic service—occupations with lower pay and status. Women, who comprised 17% of operators in 1940 but 31% by 1950, increasingly *entered* the occupation even as others left, suggesting it served as a labor market entry point for women joining the postwar workforce. New York City, home to the densest elevator market and the strongest unions, retained operators far longer than other cities: the exit rate was 79% compared with 86% elsewhere.

This paper contributes to the economics of automation (Acemoglu and Restrepo, 2020; Autor et al., 2003; Frey and Osborne, 2017), the history of occupational change (Goldin and Katz, 2008; Derenoncourt, 2022; Abramitzky et al., 2021), the political economy of technology adoption (Mokyr, 1992; David, 1990; Comin and Hobijn, 2010), and the growing literature using text as data to measure public discourse (Gentzkow et al., 2019; Dell et al., 2023). The elevator operator case documents that displacement did not follow naturally from technological capability. The descriptive patterns are consistent with automation being mediated by institutions (unions, building codes), economics (retrofit costs, labor supply), culture (tenant preferences, safety concerns), and demography (who does the job may shape how quickly society is willing to eliminate it)—though our analysis cannot isolate the causal contribution of any single factor.

## 2. Historical Background

### 2.1 The Technology

The elevator itself dates to the 1850s, when Elisha Otis demonstrated the safety brake that made passenger elevators feasible (Goodwin, 2001). For the next half-century, elevators required skilled operators who controlled speed, alignment, and door mechanisms using manual lever or wheel controls. The operator was not merely pressing buttons; they were piloting a machine whose smooth operation depended on acquired skill.

Automatic elevator technology developed rapidly in the early twentieth century. The Otis Elevator Company introduced an "Automatic Signal Control" system as early as 1924, and by the late 1920s, fully automatic push-button elevators were being installed in new residential buildings (Goodwin, 2001). The technology worked: self-service elevators were safe, reliable, and cheaper to operate. Yet building owners, tenants, and municipalities resisted the transition for decades.

### 2.2 Institutional Resistance

Several institutional factors delayed automation. First, labor unions—particularly Local 32B of the Building Service Employees International Union in New York City—negotiated contracts that required operators in existing buildings regardless of elevator technology (Gray, 2013). The union's power was concentrated in dense urban markets where elevator operators were numerous enough to organize effectively. Second, municipal building codes in many cities required attendants in passenger elevators, a regulation that persisted in some jurisdictions into the 1960s. Third, retrofit costs were non-trivial: converting a manually operated elevator to automatic service required new control systems, door mechanisms, and safety interlocks, creating a capital expenditure that building owners were reluctant to make when labor was cheap and plentiful.

Perhaps most importantly, tenants and building managers perceived operator-run elevators as safer and more prestigious. The operator served multiple functions beyond transportation: doorkeeper, security guard, package handler, and social presence. Residential buildings in particular marketed operator service as a luxury amenity, a practice that persists in a handful of buildings to this day.

### 2.3 The 1945 Strike

The tension between available technology and institutional resistance reached a crisis point on September 1, 1945, when seventeen thousand elevator operators walked off the job in New York City. The five boroughs came to a halt. Office workers climbed thirty flights of stairs. 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 decades: why were human operators still running machines that could run themselves?

The strike was resolved through collective bargaining, but it marked a turning point. Building owners and tenants who had tolerated manual operation as the status quo now had a vivid demonstration of their vulnerability. The newspaper coverage—which we analyze in the next section—shifted perceptibly after 1945: where earlier articles had debated whether automatic elevators *could* work, post-strike coverage increasingly debated whether cities *should* continue paying workers to do what machines could do.

### 2.4 Demographic Context

Elevator operation was one of the more accessible positions in the urban service economy. It required no formal education and minimal training, making it a point of entry for workers excluded from higher-skilled occupations by racial discrimination, limited education, or recent immigration. In 1940, 19% of elevator operators were Black in the full-count census—substantially higher than their 10% share of the national workforce—and 17% were women.[1] The occupation paid modestly but steadily: its OCCSCORE of 20 placed it squarely in the middle of the building service sector.

The racial composition of the occupation is central to understanding both its persistence and its displacement. When an occupation is disproportionately filled by marginalized workers, society may be more willing to eliminate those jobs—and less concerned about where displaced workers end up. The elevator operator case provides evidence for this hypothesis.

## 3. The Newspaper Record: How America Talked About Automating Elevators

Before turning to census data on what happened to elevator operators, we examine what Americans *said* about them. Public discourse both reflects and shapes the social acceptability of automation, and the newspaper record offers a window into how the cultural meaning of the elevator operator evolved over the first six decades of the twentieth century.

### 3.1 Data and Method

We draw on the American Stories corpus (Dell et al., 2023), which provides article-level text from approximately 20 million digitized newspaper pages spanning 1774 to 1963. We search 14 strategically sampled years (1900, 1905, 1910, 1915, 1920, 1925, 1930, 1935, 1940, 1945, 1946, 1950, 1955, 1960) using OCR-tolerant regular expressions designed to capture references to elevator operators and automation despite the character recognition errors common in historical newspaper digitization. Our primary search pattern, `[ec]l[ec]vat[oa]r`, captures the most frequent OCR substitution errors (e↔c, o↔a) while remaining sufficiently specific to avoid excessive false positives. This yields 71,894 matched articles across all sampled years.

A critical methodological challenge is disambiguating *building* elevators from *grain* elevators. We implement a two-stage filtering system. First, articles containing high-signal phrases unambiguously related to building elevators ("elevator operator," "elevator boy," "automatic elevator," "elevator strike," "push-button elevator") are retained directly. Second, articles matching only the broad pattern are checked against a grain-context dictionary ("bushel," "grain elevator," "wheat," "harvest") and excluded if grain references predominate. We then classify the retained building-elevator articles into five thematic categories—AUTOMATION,

[1] The linked panel (Section 4.3) shows a Black share of 15.6%, lower than the 19% in the full-count cross-section, because the census linking algorithm has lower match rates for Black individuals (Abramitzky et al., 2021).

LABOR, STRIKE, ACCIDENT, and CONSTRUCTION—using a deterministic keyword dictionary that requires thematic keywords to co-occur with elevator-related context (see Section B for the full dictionary and validation results). This yields 7,458 thematically classified building-elevator articles. The remaining articles mention elevators incidentally and are classified as OTHER.

Because the American Stories corpus varies in coverage across years—reflecting the irregular digitization of the underlying Chronicling America collection—raw article counts confound genuine changes in discourse with changes in corpus size. We address this by computing total article counts for each sampled year and expressing elevator coverage as a rate per 10,000 corpus articles (Figure 1, Panel B).

### 3.2 The Arc of Public Discourse

Figure 1 presents the quantitative anatomy of how American newspapers discussed elevators over six decades. Panel A shows the thematic composition of classified building-elevator articles. Panel B shows the corpus-normalized elevator mention rate. Together, they reveal three phases of discourse.

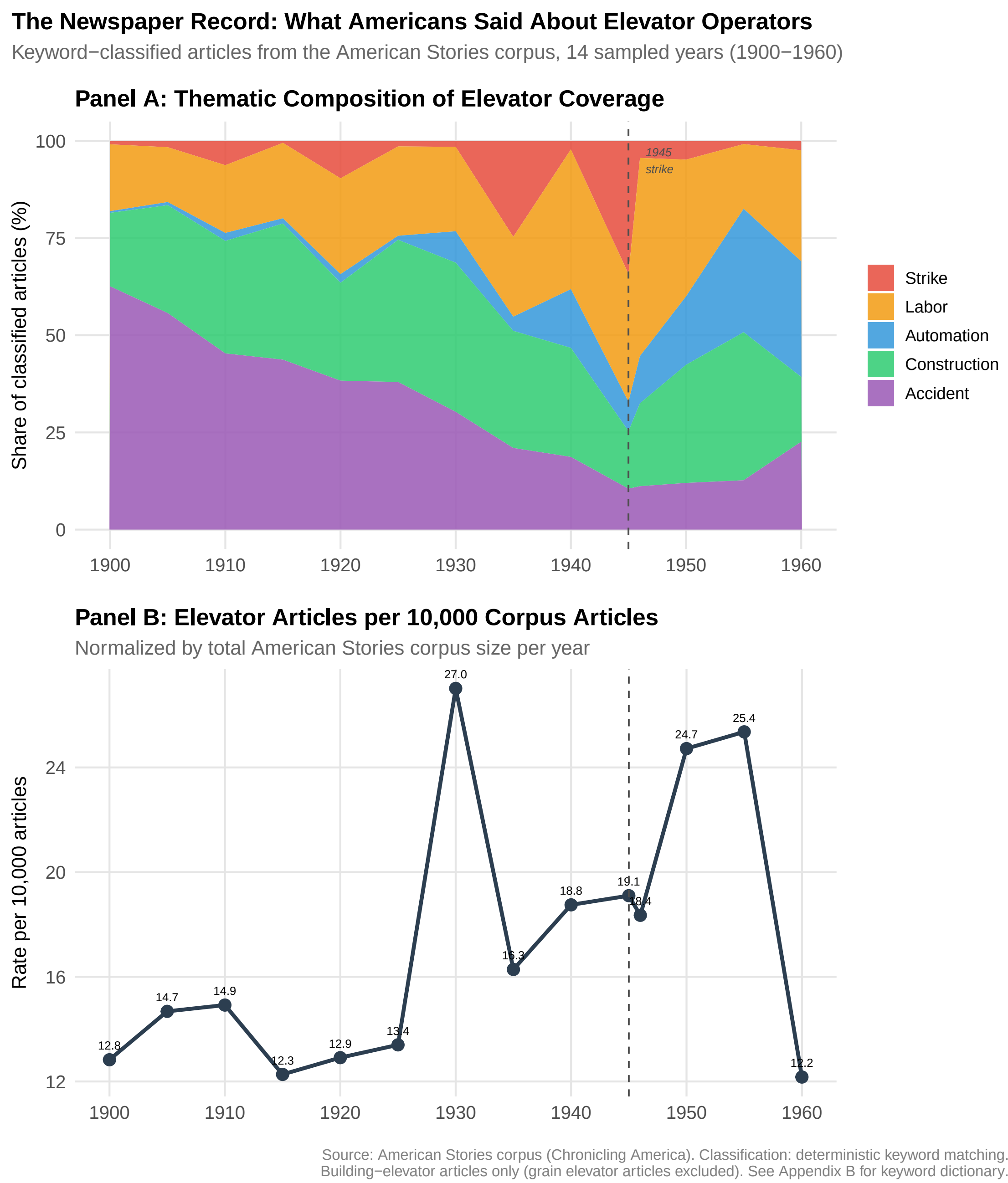


**Figure 1:** Newspaper Coverage of Elevator Operators: Thematic Composition and Corpus-Normalized Volume

Source: American Stories corpus (Dell et al., 2023). Articles classified using deterministic keyword matching into five thematic categories. Panel B normalizes elevator-related articles by total corpus size per sampled year. Dashed line marks the 1945 NYC elevator strike. See Section B for classification methodology and validation.

In the early decades, accident coverage dominated. Between 1900 and 1915, accidents accounted for the largest share of classified articles—reflecting both the genuine dangers of early elevator technology and the newsworthiness of building mishaps. Labor coverage was the second-largest category, driven by the early organizing efforts of building service workers. Automation coverage was negligible: fewer than 40 articles per sampled year mentioned automatic elevators before 1920.

The thematic composition shifted in the 1920s and 1930s as accident coverage declined and automation stories emerged. Articles about "push-button elevators" installed in modern buildings framed automation as novelty, not threat. Meanwhile, labor coverage grew as elevator operators unionized in major cities, generating a parallel narrative about the growing organizational power of the workers themselves.

The 1945 New York City elevator strike was a watershed (Figure 2). Strike and labor articles spiked sharply: in 1945, labor-related coverage exceeded accident coverage for the first time, and strike articles reached their all-time peak. The strike generated over 2,100 elevator-related articles in a single year—a volume driven not by routine coverage but by the existential question the strike posed: why were human operators still running machines that could run themselves?

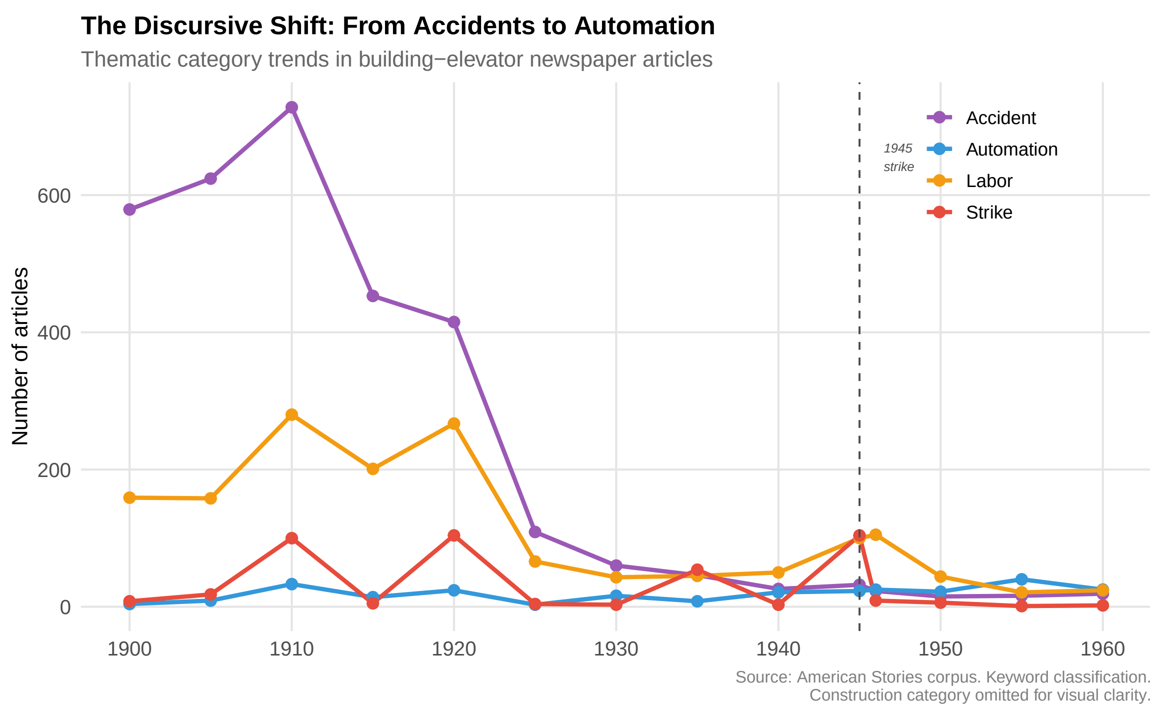


**Figure 2:** The Discursive Shift: Thematic Category Trends in Elevator Coverage

Source: American Stories corpus. Keyword-classified building-elevator articles. Construction category omitted for visual clarity. Dashed line marks the 1945 NYC elevator strike.

After 1945, accident and labor coverage both collapsed. Automation coverage, though never large in absolute terms, became a larger share of the shrinking total. By 1955 and

1960, elevator stories were rare in any category—the occupation had become too marginal to generate news. The corpus-normalized rate (Panel B of Figure 1) confirms that the decline is not an artifact of corpus coverage: elevator articles per 10,000 corpus articles fell from their peak in the early 1900s to their lowest levels by 1960.

### 3.3 Geographic Variation in Discourse

The newspaper record reveals geographic heterogeneity that mirrors the occupational data. Figure 3 shows article volume over time for the cities with the most elevator coverage.

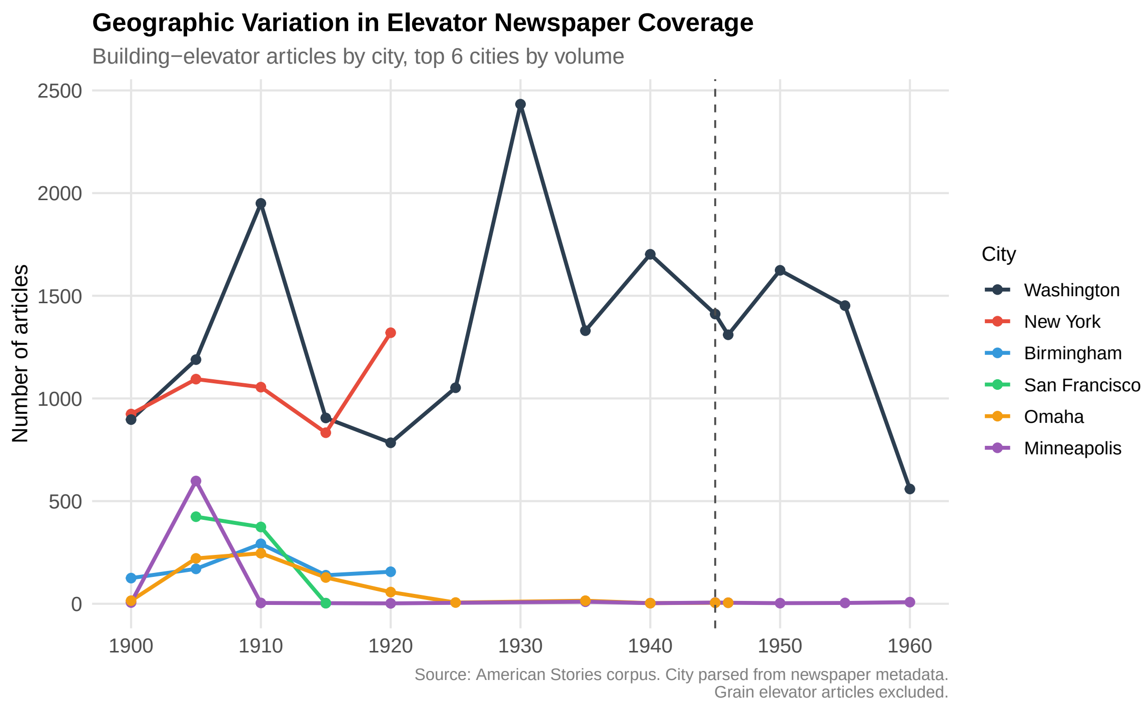


**Figure 3:** Geographic Variation in Elevator Newspaper Coverage

Source: American Stories corpus. City identified from newspaper metadata (publication location). Building-elevator articles only.

Washington, D.C., dominates the newspaper record—a reflection of the *Evening Star*'s extensive coverage and D.C.'s extraordinary concentration of elevator operators (58.4 per 10,000 employed in 1940, the highest in the nation). New York City papers covered elevator operators intensively during the strike years but less consistently otherwise. Cities in the Midwest and South, where elevator operators were fewer and less unionized, generated less coverage overall.

The geographic pattern has an important implication for interpreting the timing of discourse. D.C.'s dominance in the newspaper data means that the aggregate time series partly reflects federal government employment patterns—where civil service protections slowed conversion to automatic elevators—rather than the private-sector dynamics that drove displacement in most cities.

### 3.4 Discourse and Occupational Decline

The timing of the discursive shift is suggestive, though we cannot establish causality from sampled newspaper coverage. The evidence is consistent with a three-stage process: (1) a period of unquestioned coexistence, during which the occupation and its replacement technology are both present but automation is not discussed as a policy question (1900–1930s); (2) a period of active debate, during which automation enters public discussion but the occupation remains stable or growing (1930s–1950); and (3) a period of accepted decline, during which the discourse fades entirely as the occupation collapses (1950–1980).

This sequencing—discursive change preceding occupational decline—is consistent with the interpretation that automation involves cultural and institutional processes, not merely technological substitution. The automatic elevator was a necessary condition for eliminating the operator, but it was not sufficient. What also appears to have been required was a shift in public framing: from viewing the operator as a trusted service provider to viewing the operator as an unnecessary expense. An alternative interpretation, which we cannot rule out, is that the discourse reflected building owners' strategic efforts to shape public opinion in anticipation of automation they were already planning (Mokyr, 1992). In either case, the newspapers document a real-time evolution in how Americans discussed the acceptability of eliminating a familiar occupation.

## 4. Data

### 4.1 Census Microdata (1900–1950)

To track the disappearance of the elevator operator, we follow 680 million person-records across six decennial censuses from 1900 to 1950, drawn from the IPUMS full-count census files (Ruggles et al., 2024). We identify elevator operators using the harmonized OCC1950 code 761 and compute all rates relative to the employed labor force after excluding individuals with special OCC1950 codes (0, 979–999) that represent persons outside the occupation structure.[2]

[2]Special codes include: 0 (not in labor force/no occupation), 979 (not yet classified), 980–987 (experienced worker, no current job), 990 (new worker), 995 (unpaid family worker), and 999 (not reported). These codes affected 8–14% of person-records depending on the census year, inflating denominators and understating per-capita occupation rates. See Section A for sensitivity analysis.

For comparison, we track five other building service occupations—janitors (OCC1950 770), porters (780), guards/doorkeepers (763), charwomen/cleaners (753), and housekeepers (764)—that shared similar skill requirements and demographic profiles but were not subject to the same automation pressure.

### 4.2 Published Census Aggregates (1960–1980)

For the post-1950 period, we use published aggregate counts from the Census of Population, Detailed Characteristics volumes (U.S. Bureau of the Census, 1963–1984). These provide counts of elevator operators and comparison occupations alongside total civilian employment, enabling us to extend the lifecycle through the extinction phase. We prefer published aggregates over Public Use Microdata Samples for this purpose because the occupation was declining rapidly and sample-based estimates for 1970 and 1980 would be imprecise.

The published sources report 66,530 elevator operators in 1960 (10.3 per 10,000 employed), 24,860 in 1970 (3.2), and 7,340 in 1980 (0.8). The 1980 figure—almost exactly the 1900 count—marks the effective extinction of the occupation.

### 4.3 Linked Panel (1940–1950)

We track individual elevator operators across a decade using the IPUMS Multigenerational Longitudinal Panel (MLP) v2.0 (Ruggles et al., 2021), which provides probabilistic links between census records based on name, age, birthplace, and race. From the 1940 full-count census, we identify 82,666 elevator operators. The MLP links 38,562 of these to 1950 census records—a linkage rate of 47%. While imperfect, this rate is comparable to other linked historical census studies and is substantially higher than rates achieved with deterministic linking alone (Abramitzky et al., 2021; Bailey et al., 2020).

To assess whether linked individuals are representative, we estimate a logit model of linkage probability as a function of observable characteristics (age, race, sex, nativity, marital status, NYC residence). We find that older, male, and married individuals are more likely to be linked—a standard pattern reflecting the difficulty of linking women who change surnames and young workers who are harder to disambiguate (Bailey et al., 2020). We address this selection through inverse probability weighting in robustness checks (Section 8).

For comparison, we also link building service workers in adjacent occupations (janitors, porters, guards/doorkeepers, charwomen/cleaners, and housekeepers) to construct a comparison group for displacement regressions. Section 4.3 presents summary statistics for both groups. Elevator operators were younger (36 vs. 44), and far more concentrated in New York City (30% vs. 8%) than comparison workers. Both groups had similar baseline

OCCSCORE values (≈20), but their 1950 outcomes differed: operators experienced smaller OCCSCORE declines (−0.95 vs. −3.34), suggesting that despite similar exit rates (84% vs. 83%), operators moved to somewhat better destinations on average—though this masks profound heterogeneity by race.

**Table 1:** Summary Statistics: Linked Panel, 1940 Characteristics

| | Elevator Operators | | Comparison Workers | |
|---|---|---|---|---|
| Variable | Mean | SD | Mean | SD |
| Age | 36.0 | 13.3 | 43.6 | 14.3 |
| Female (%) | 13.5 | | 15.1 | |
| Black (%) | 15.6 | | 19.2 | |
| Native-born (%) | 77.4 | | 80.6 | |
| NYC resident (%) | 29.5 | | 8.2 | |
| OCCSCORE (1940) | 20.0 | 0.0 | 19.9 | 3.3 |
| *1950 Outcomes* | | | | |
| Changed occupation (%) | 84.2 | | 83.2 | |
| Interstate mover (%) | 8.4 | | 7.9 | |
| OCCSCORE change | −0.95 | 12.4 | −3.34 | 12.9 |
| N | 38,562 | | 445,211 | |

*Note:*
Source: IPUMS Full-Count Census + MLP v2.0. Comparison workers: janitors (OCC1950 770), porters (780), guards/doorkeepers (763), charwomen/cleaners (753), housekeepers (764). Linked sample (1940 to 1950). SD omitted for binary variables.

### 4.4 County and Metropolitan Area Data

We aggregate the full-count microdata to the county level using COUNTYICP codes to construct a geographic panel spanning 1900–1950. We identify 23 major metropolitan areas through county-to-metro crosswalks, including the five New York City boroughs (Manhattan = COUNTYICP 610, Brooklyn = 470, Queens = 810, Bronx = 050, Staten Island = 850). This geographic detail enables us to analyze the spatial concentration of the occupation and the variation in displacement across local labor markets.

### 4.5 American Stories Newspaper Corpus

The newspaper analysis described in Section 3 uses article-level data from the American Stories corpus (Dell et al., 2023), accessed via HuggingFace. The corpus covers approximately

20 million newspaper scans from 1774 to 1963, with article-level segmentation and OCR text extraction. We process 14 strategically sampled years (1900–1960) spanning the full lifecycle of the occupation, yielding 71,894 matched elevator-related articles, of which 7,458 are classified into five thematic categories using a deterministic keyword dictionary requiring elevator co-occurrence. See Section B for details on keyword strategy, corpus normalization, geographic identification, and classification validation.

## 5. The Full Arc: Rise, Plateau, and Extinction

Figure 4 presents the central descriptive fact of the paper: the complete lifecycle of the elevator operator from 1900 to 1980, measured as operators per 10,000 employed workers.

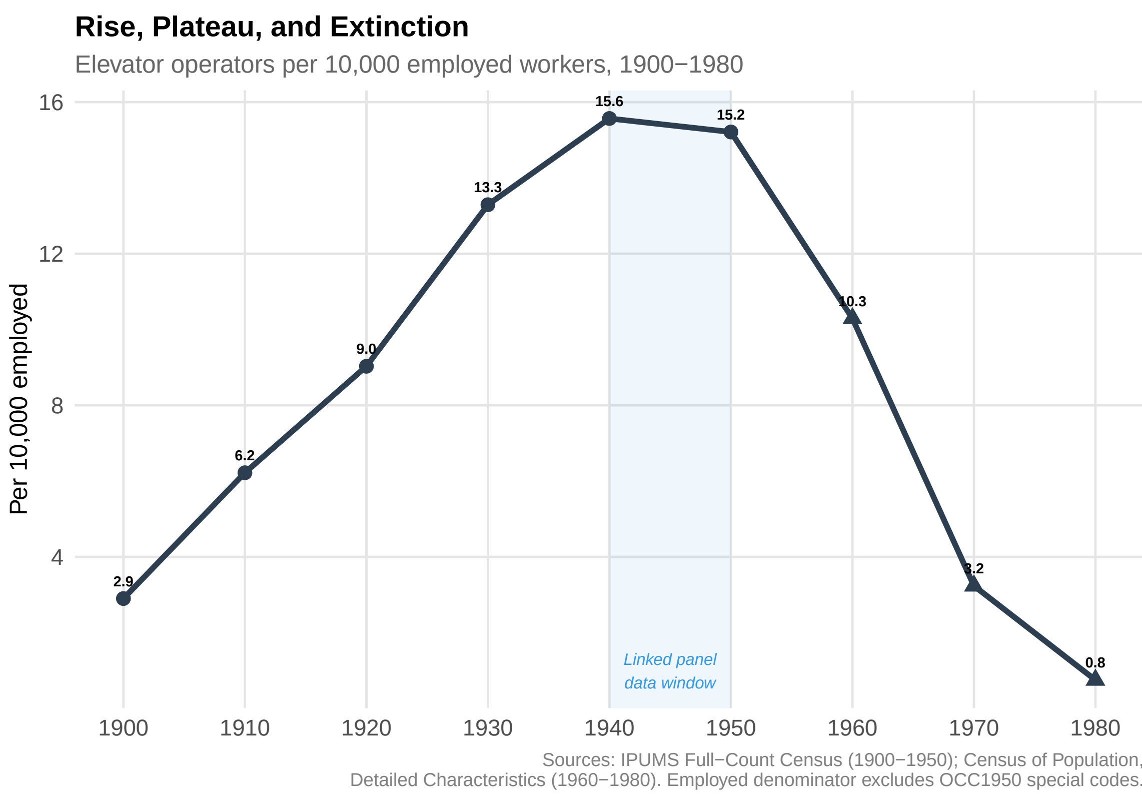


**Figure 4:** Rise, Plateau, and Extinction: Elevator Operators per 10,000 Employed, 1900–1980

Sources: IPUMS Full-Count Census (1900–1950); Census of Population, Detailed Characteristics (1960–1980). Employed denominator excludes OCC1950 special codes. The shaded region marks the linked panel window (1940–1950).

The arc has three distinct phases. First, a four-decade **rise** from 2.9 per 10,000 in 1900 to 15.6 in 1940, driven by the building boom of the 1920s and the proliferation of multi-story commercial and residential structures in growing cities. The number of operators grew from

7,943 to 82,666—a factor of ten—while the employed labor force roughly doubled. Second, a brief **plateau** between 1940 (15.6 per 10,000) and 1950 (15.2 per 10,000), during which total numbers were essentially flat (82,666 to 85,294) but the rate began a barely perceptible decline as the employed labor force grew. Third, a rapid **extinction** from 1950 to 1980, during which the rate fell from 15.2 to 0.8 per 10,000—a 95% decline in three decades.

This trajectory is unique among building service occupations. Figure 5 shows that janitors, porters, and guards—which shared the same workplaces, similar skill requirements, and overlapping demographics—followed entirely different paths. Janitors grew monotonically across the entire period, reaching 214 per 10,000 by 1980. Guards doubled. Only porters declined, and gradually, without the abrupt collapse that characterizes the elevator operator.

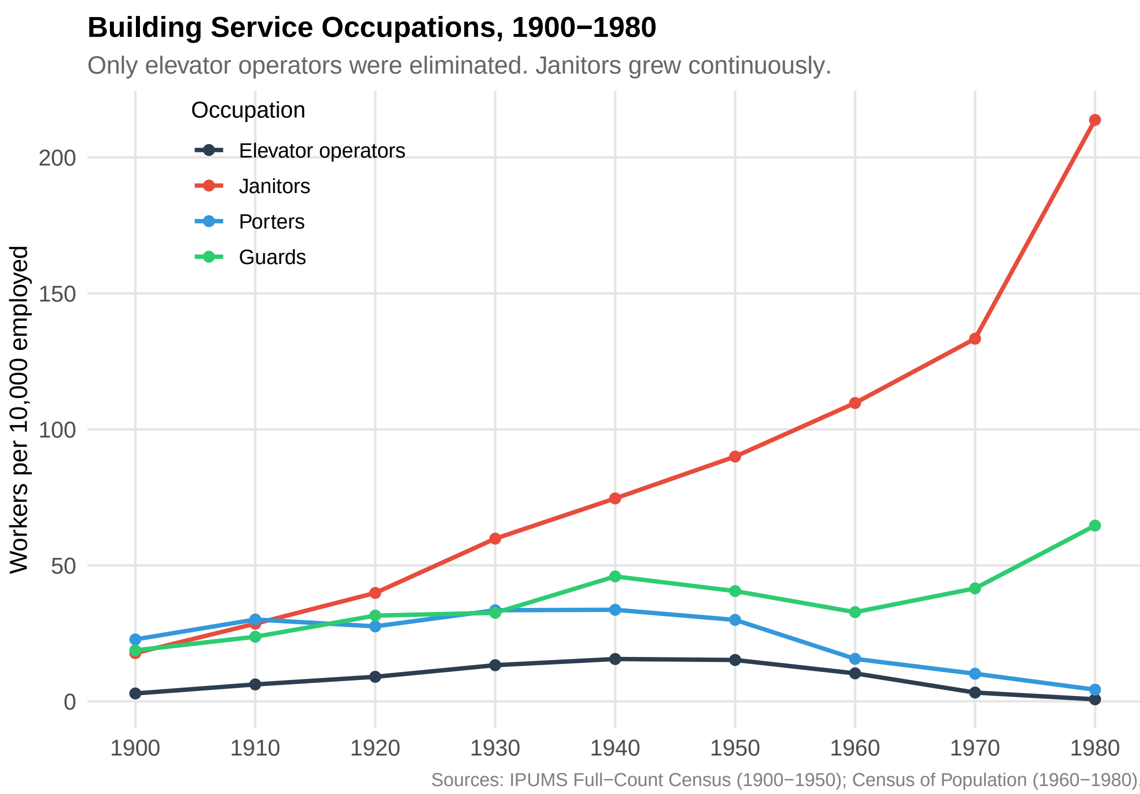


**Figure 5:** Elevator Operators vs. Comparison Occupations per 10,000 Employed, 1900–1980

Sources: Same as Figure 4. Comparison occupations: janitors (OCC1950 770), porters (780), guards/doorkeepers (763).

### 5.1 National Trends

Section 5.1 summarizes the national trajectory. In raw numbers, the occupation grew from fewer than 8,000 to over 85,000, with the absolute count peaking in 1950 (85,294) before falling to 7,340 by 1980—almost exactly back to its 1900 level. But the normalized *rate* peaked earlier: 15.6 per 10,000 employed in 1940, declining to 15.2 in 1950. The plateau in raw counts masked the beginning of relative decline, as the employed labor force grew faster than the number of operators.

**Table 2:** Rise, Plateau, and Extinction: Elevator Operators in the United States, 1900–1980

| Year | Total operators | Per 10k employed | Source |
|---|---|---|---|
| 1900 | 7,943 | 2.9 | Full-count |
| 1910 | 23,376 | 6.2 | Full-count |
| 1920 | 36,437 | 9.0 | Full-count |
| 1930 | 62,676 | 13.3 | Full-count |
| 1940 | 82,666 | 15.6 | Full-count |
| 1950 | 85,294 | 15.2 | Full-count |
| 1960 | 66,530 | 10.3 | Published |
| 1970 | 24,860 | 3.2 | Published |
| 1980 | 7,340 | 0.8 | Published |

*Note:*
Sources: IPUMS Full-Count Census (1900–1950); Census of Population, Detailed Characteristics (1960–1980). Employed denominator excludes OCC1950 special codes (0, 979–999).

### 5.2 Demographic Shifts

The composition of the occupation changed dramatically across the arc. The female share rose from 1.5% in 1900 to 17% in 1940 and then surged to 31% by 1950 (Figure 6). The Black share fluctuated between 19% and 25% across the period but showed an important temporal pattern: it fell from 25% in 1930 to 19% in 1940 as white workers entered during the Depression, then rose back to 25% by 1950 as white workers left for better postwar opportunities. This "last hired, first fired" pattern—with the racial composition responding to business cycle conditions—is consistent with the occupation serving as a residual employer for workers facing discrimination in other sectors.

Mean age rose steadily from 26 in 1900 to 44 in 1950, reflecting both the aging of incumbent operators and the declining entry of young workers. By 1950, the modal elevator operator was a middle-aged woman or an older Black man—a demographic profile that suggests the occupation had become a refuge rather than a stepping stone.

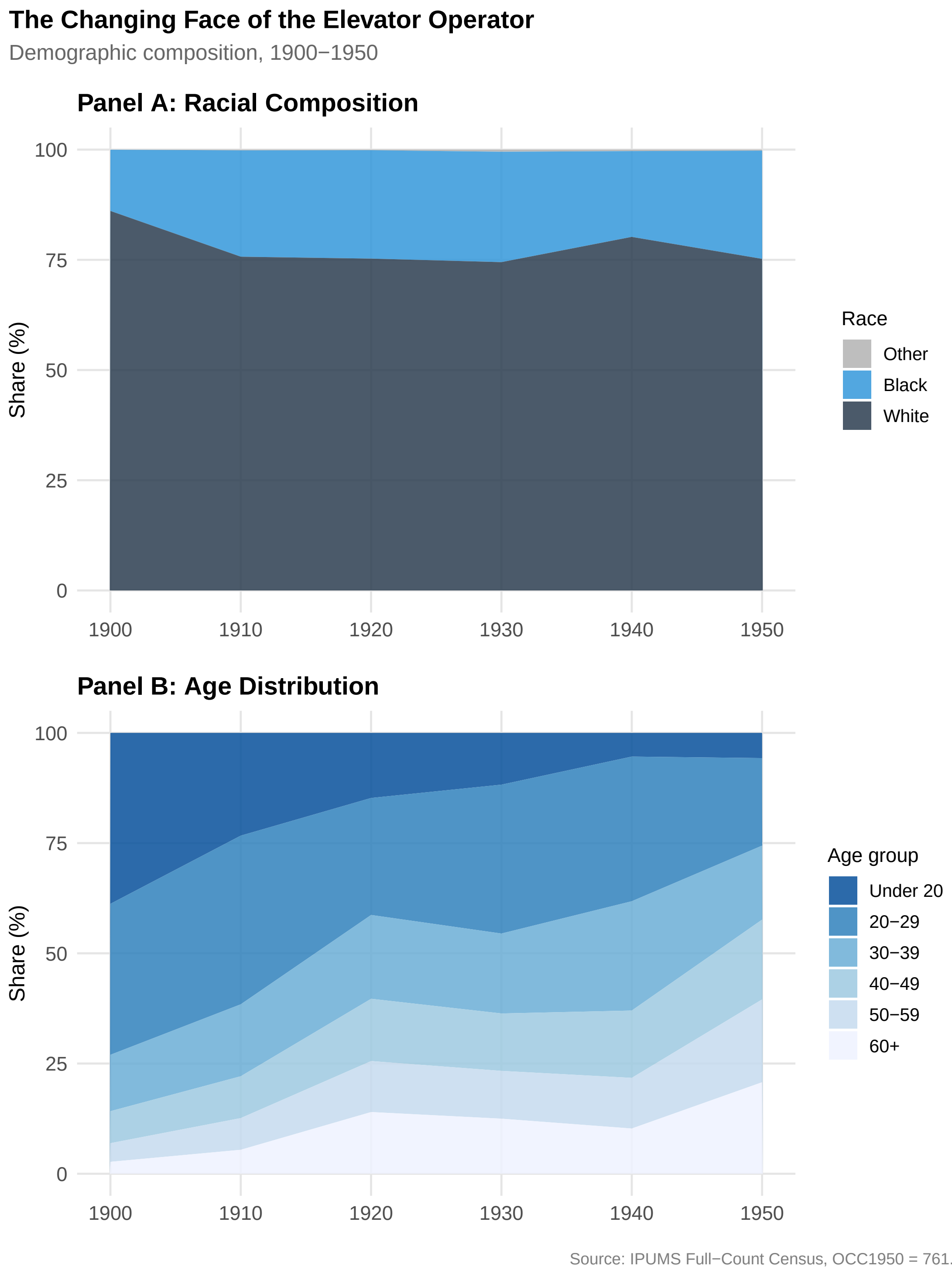


**Figure 6:** Demographic Composition of Elevator Operators, 1900–1950

Source: IPUMS Full-Count Census 1900–1950. Percent Black and percent female among all elevator operators (OCC1950 = 761).

### 5.3 Geographic Concentration

Elevator operators were not evenly distributed across the country. They were an overwhelmingly urban occupation, concentrated in the cities with the tallest buildings and the densest commercial districts. Figure 7 shows state-level operator density in 1920, 1940, and 1950. The occupation was most concentrated in New York, New Jersey, Illinois, and the District of Columbia—states containing the major commercial centers.

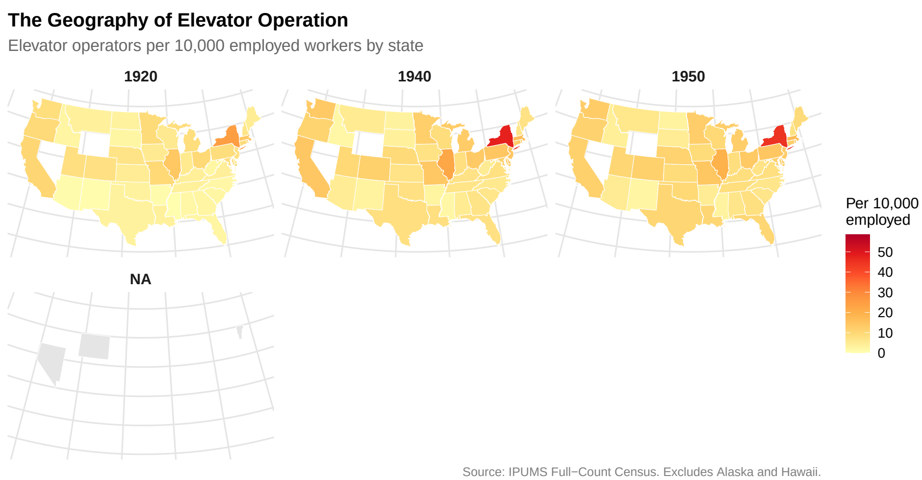


**Figure 7:** Elevator Operators per 10,000 Employed by State, 1920–1950

Source: IPUMS Full-Count Census. Contiguous United States only (Alaska and Hawaii excluded as non-states during this period). Grey shading indicates states with fewer than 100 employed workers (data suppressed).

At the metropolitan level, the concentration was extreme. Section 5.3 presents the top 15 metropolitan areas by operator count in 1940 and 1950. New York City alone employed more than 25,000 elevator operators in 1940—nearly a third of the national total. Washington, D.C. had the highest rate per 10,000 employed (58.4), reflecting the concentration of large government and commercial buildings. The change from 1940 to 1950 varied dramatically across cities: some (Washington, Los Angeles) actually grew, while others (Chicago, New York) began contracting.

**Table 3:** Elevator Operators in Major Metropolitan Areas, 1940 vs. 1950

| | 1940 | | 1950 | | |
|---|---|---|---|---|---|
| Metro | 1940 (N) | 1940 (per 10k) | 1950 (N) | 1950 (per 10k) | Change (%) |
| New York City | 25,484 | 74.6 | 23,506 | 71.7 | -3.8 |
| Chicago | 6,535 | 35.1 | 5,578 | 29.3 | -16.5 |
| Los Angeles | 2,205 | 18.1 | 2,303 | 14.4 | -20.2 |
| Washington DC | 2,007 | 58.4 | 2,077 | 56.4 | -3.4 |
| Detroit | 1,809 | 20.5 | 1,894 | 19.3 | -6.0 |
| Cleveland | 1,219 | 22.7 | 1,254 | 22.1 | -2.4 |
| St. Louis | 1,202 | 31.9 | 1,149 | 31.5 | -1.2 |
| Boston | 1,199 | 32.6 | 1,394 | 39.1 | +19.8 |
| Baltimore | 727 | 18.8 | 787 | 20.4 | +8.6 |
| Minneapolis | 720 | 28.3 | 685 | 24.8 | -12.4 |
| Milwaukee | 677 | 20.9 | 727 | 19.5 | -7.0 |
| Newark | 605 | 16.2 | 601 | 16.1 | -0.2 |
| Indianapolis | 457 | 22.8 | 407 | 18.5 | -18.8 |
| Portland | 418 | 25.5 | 511 | 25.8 | +1.4 |
| Denver | 400 | 28.7 | 389 | 25.6 | -10.9 |

*Note:*
Source: IPUMS Full-Count Census (cross-section, not the linked panel). Metro identified by primary county COUNTYICP. Per 10k = per 10,000 employed. Change (%) is computed from the per-10k rate.

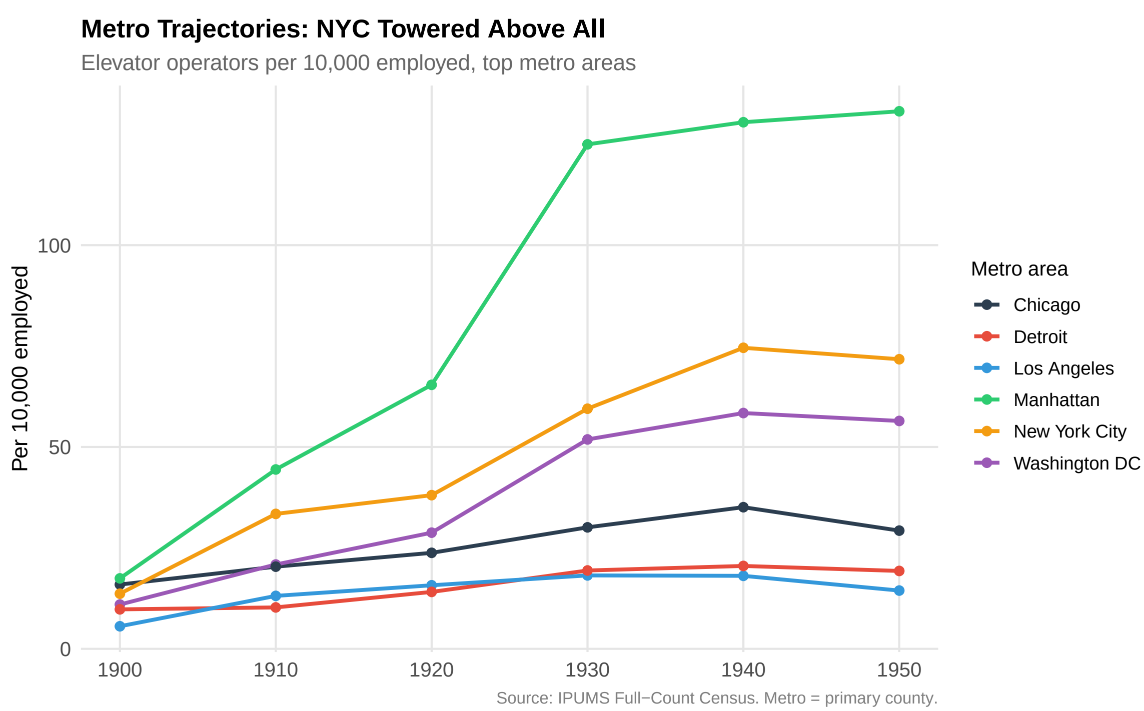


**Figure 8:** Elevator Operator Rates in Major Metropolitan Areas, 1900–1950
Source: IPUMS Full-Count Census. County-level data aggregated to metro areas. Per 10,000 employed.

## 6. Who Enters, Who Exits: Individual Displacement, 1940–1950

The cross-sectional data establish that the elevator operator rate peaked in 1940 and began declining, even as raw counts remained flat through 1950. But aggregate statistics conceal enormous individual-level churning. Using linked census records, we can track where displaced operators ended up—and who replaced them.

### 6.1 The Transition Matrix

Of the 38,562 elevator operators in 1940 that we link to 1950 records, 32,456 (84%) had exited the occupation by 1950. This exit rate was not exceptional: 81% of janitors, 83% of porters, and 84% of guards also changed occupations over the same decade, reflecting the enormous labor market churn of the 1940s (wartime mobilization, postwar reconversion, and rapid sectoral reallocation). What distinguishes elevator operators is not *whether* they left, but *where they went*. Section 6.1 shows their destinations. Only 16% remained elevator operators. Another 16% had left the labor force entirely. Among those who transitioned to new occupations, the most common destinations were miscellaneous other occupations (13.5%), operative/manufacturing work (12.7%), craft positions (12.2%), and farm work (11.0%).

**Table 4:** 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. N = 38,562 elevator operators in 1940 linked to 1950 census.

The direction of these transitions varied substantially (Figure 9). Using the OCC1950 prestige score (OCCSCORE) as a measure of occupational quality, we classify movements as upward (higher OCCSCORE), lateral (similar), or downward (lower). Forty-four percent of exiting operators moved to higher-prestige occupations, while 12% moved downward. But these averages mask profound heterogeneity by race.

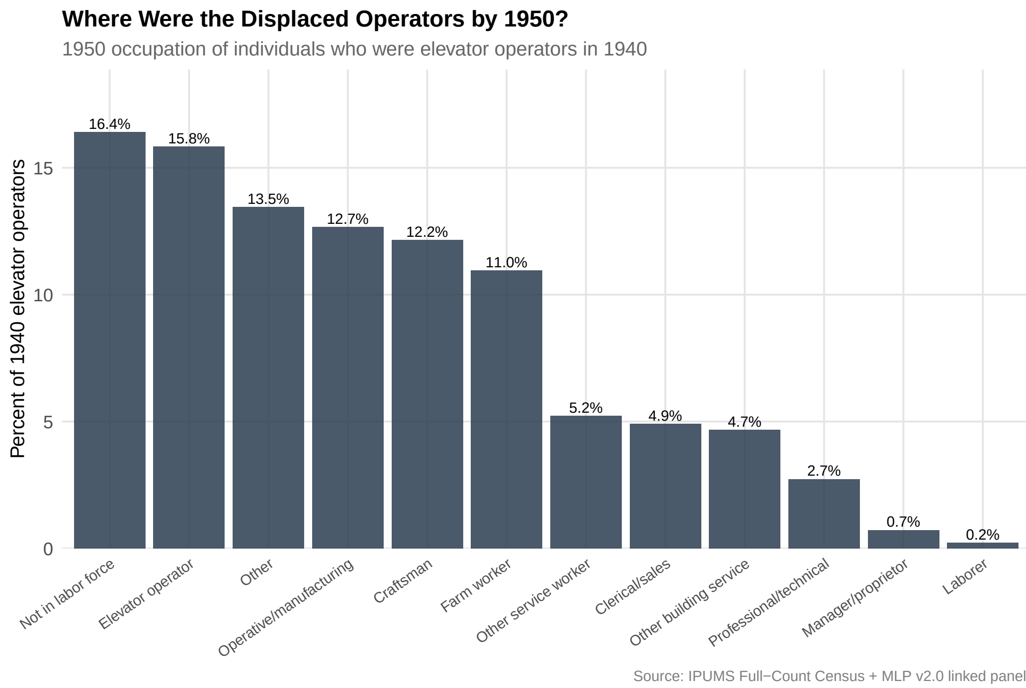


**Figure 9:** Occupational Transitions of 1940 Elevator Operators by 1950

Source: IPUMS + MLP v2.0 linked panel. N = 38,562. Categories based on OCC1950 broad groupings.

### 6.2 Racial Channeling

Figure 10 presents the starkest finding in the paper. Among white elevator operators who exited, 13% moved into craft positions and 5% into clerical or sales work—occupations with higher OCCSCORE values representing genuine upward mobility. Among Black operators who exited, only 6% reached craft positions and 3% reached clerical or sales work. Instead, Black operators were disproportionately channeled into other building service work (10% vs. 4% for whites) and farm labor (14% vs. 10%).

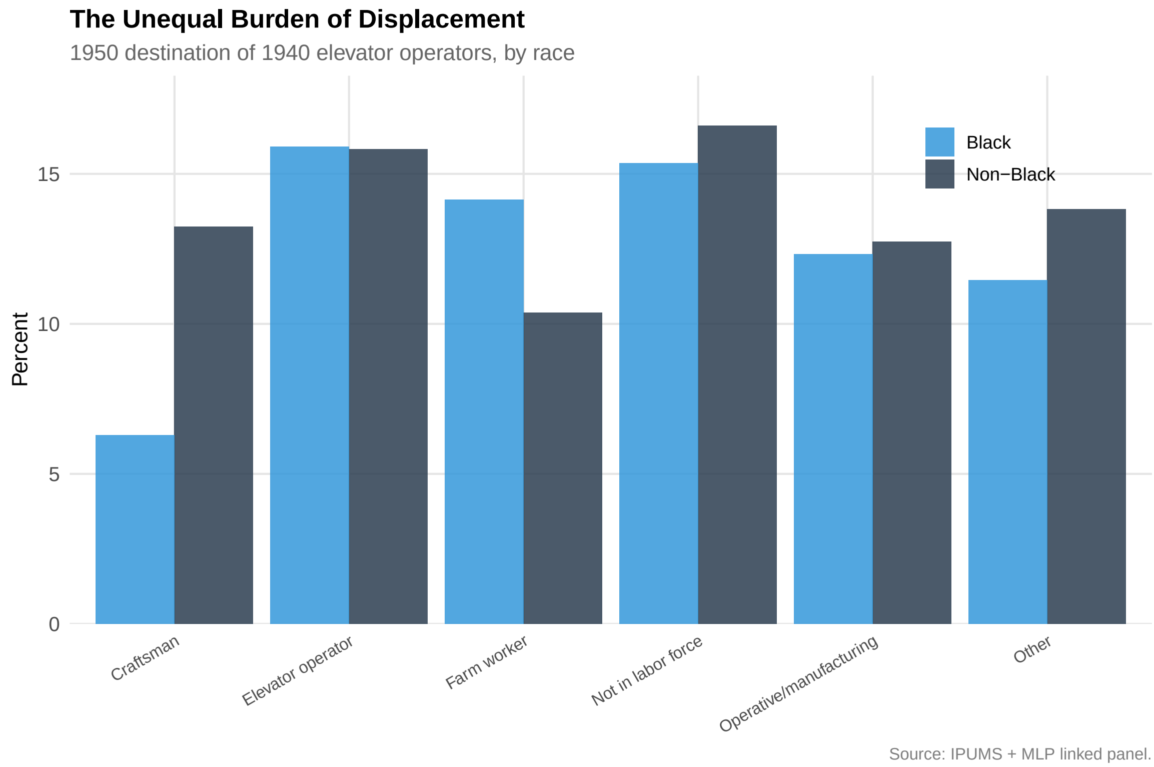


**Figure 10:** Occupational Destinations by Race: 1940 Elevator Operators in 1950
Source: IPUMS + MLP v2.0 linked panel. White: N = 32,566. Black: N = 5,996.

This pattern of racial channeling is not explained by observable differences in human capital. We estimate linear probability models of the form:

$$Y_i = \alpha + \beta \cdot \text{ElevatorOperator}_i + X_i'\gamma + \delta_s + \varepsilon_i \tag{1}$$

where $Y_i$ is a 1950 outcome (same occupation, interstate move, or OCCSCORE change) and we include fixed effects for state ($\delta_s$), race, sex, and age group (five-year bins). Standard errors are clustered by state ($S = 49$ clusters). In these regressions (Section 6.2), the coefficient on the elevator operator indicator (relative to other building service workers) is positive but small (+0.024), indicating that elevator operators' occupation persistence rate was comparable to that of janitors, porters, and guards—the comparison group also experienced substantial turnover. What matters is not whether operators left (everyone did) but *where* they ended up. Elevator operators experienced a marginally significant reduction in interstate mobility ($-0.006$) and a negative (though imprecisely estimated) change in occupational prestige. The heterogeneity regressions in Section 7 reveal that the interaction between operator status and race is large and significant: Black elevator operators were 5.7 percentage points less likely to persist than their white counterparts ($p < 0.01$), conditional on age, sex, and geography.

Table 5: 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
FE: state, race, sex, age group. SE clustered by state.

### 6.3 Who Stayed: Selection into Persistence

If 84% exited, who were the 16% that remained? Section 6.3 presents average marginal effects from a logit model of persistence. The strongest predictor is New York City residence: being in NYC in 1940 increased the probability of remaining an elevator operator by 5.1 percentage points, consistent with the institutional thickness story. Age was also strongly predictive—older operators stayed, likely because they had fewer outside options and higher occupation-specific capital. Women were 2.1 percentage points more likely to stay than men, while married workers and native-born workers were more likely to leave. Race, conditional on other observables, was not significantly associated with persistence *within* the operator sample ($p = 0.62$)—though the heterogeneity regressions in Section 7 show that relative to other building service workers, Black operators faced significantly higher displacement.

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

| Variable | Coefficient | AME | Coef. SE | p-value |
|---|---|---|---|---|
| Age (centered) | 0.1283 | 0.0153 | 0.0026 | 0.000 |
| Age$^2$ | -0.0036 | -0.0004 | 0.0001 | 0.000 |
| Black | 0.0204 | 0.0024 | 0.0415 | 0.623 |
| Female | 0.1769 | 0.0211 | 0.0472 | 0.000 |
| Native-born | -0.1704 | -0.0203 | 0.0344 | 0.000 |
| Married | -0.2300 | -0.0274 | 0.0356 | 0.000 |
| NYC resident | 0.4282 | 0.0510 | 0.0334 | 0.000 |

*Note:*
Logit model: P(still elevator operator in 1950 | elevator operator in 1940). AME = average marginal effect. SE and p-value refer to the logit coefficient, not the AME. $N = 38{,}562$ elevator operators.

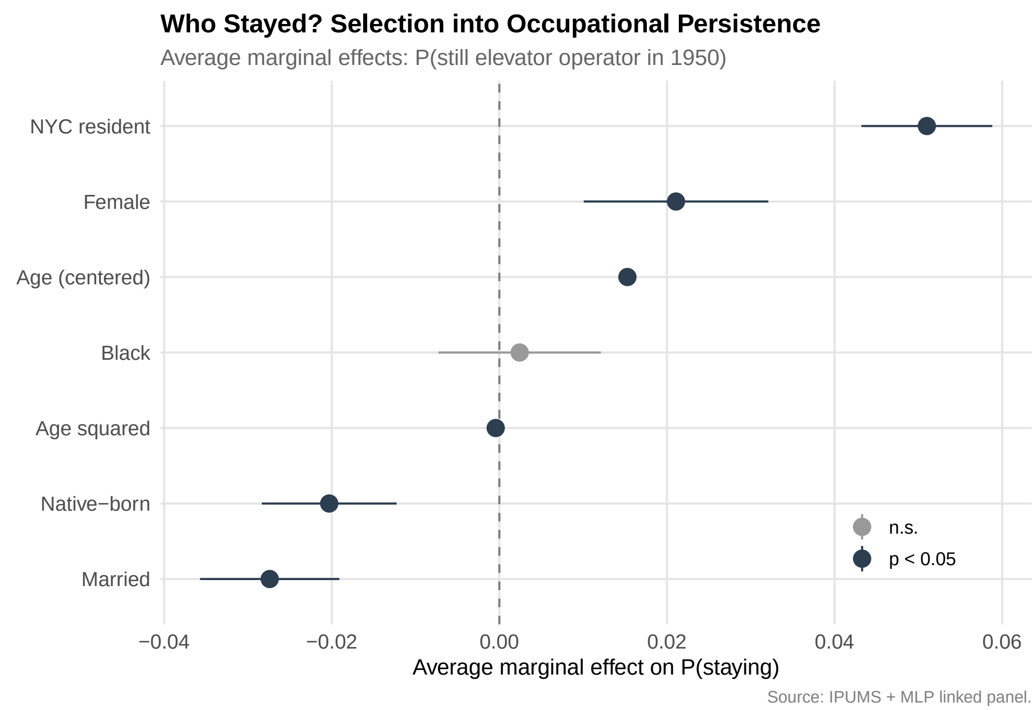


**Figure 11:** Selection into Persistence: Average Marginal Effects from Logit Model

Source: IPUMS + MLP v2.0 linked panel. N = 38,562. Dependent variable: still employed as elevator operator in 1950.

### 6.4 Who Entered: The Changing Workforce

A striking feature of the aggregate data is that the occupation barely shrank between 1940 and 1950 despite an 84% exit rate among incumbents. This implies massive entry: 36,700 individuals who were *not* elevator operators in 1940 held the title by 1950. Who were these entrants?

The entrants differed dramatically from the exiters (Figure 12). Thirty percent were women, compared with 14% among exiters—consistent with the feminization visible in the cross-sectional data. Eighteen percent were Black, compared with 15.6% in the overall 1940 linked panel (Section 4.3). Most strikingly, 40% had been outside the labor force in 1940, suggesting that elevator operation served as an entry point for workers newly joining the postwar economy. The mean OCCSCORE gain for entrants was 6.9 points—elevator operation, at OCCSCORE 20, was a step *up* for workers coming from agricultural labor, domestic service, or non-employment.

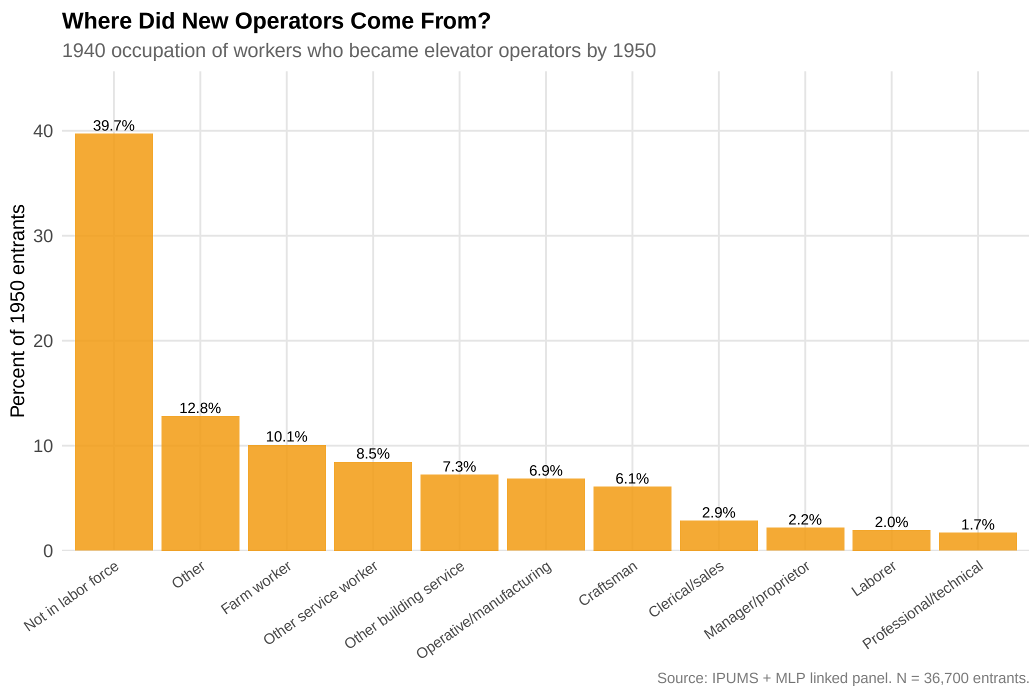


**Figure 12:** Prior Occupations of 1950 Elevator Operators Who Were Not Operators in 1940
Source: IPUMS + MLP v2.0 linked panel. N = 36,700 entrants.

The simultaneous exit of experienced workers and entry of less-advantaged workers is a hallmark of occupational decline. As the best-positioned workers leave, the occupation's status falls, which accelerates the departure of remaining advantaged workers and attracts more disadvantaged entrants. By 1950, elevator operation was becoming a last-resort occupation—one that workers entered because they had nowhere better to go, even as others fled to superior alternatives.

### 6.5 The New York City Case

New York City provides a natural laboratory for understanding how institutional factors shaped the pace and character of displacement. With over 25,000 operators in 1940, the city employed nearly a third of the national total. Its operators were protected by union contracts, municipal building codes, and a culture of full-service buildings.

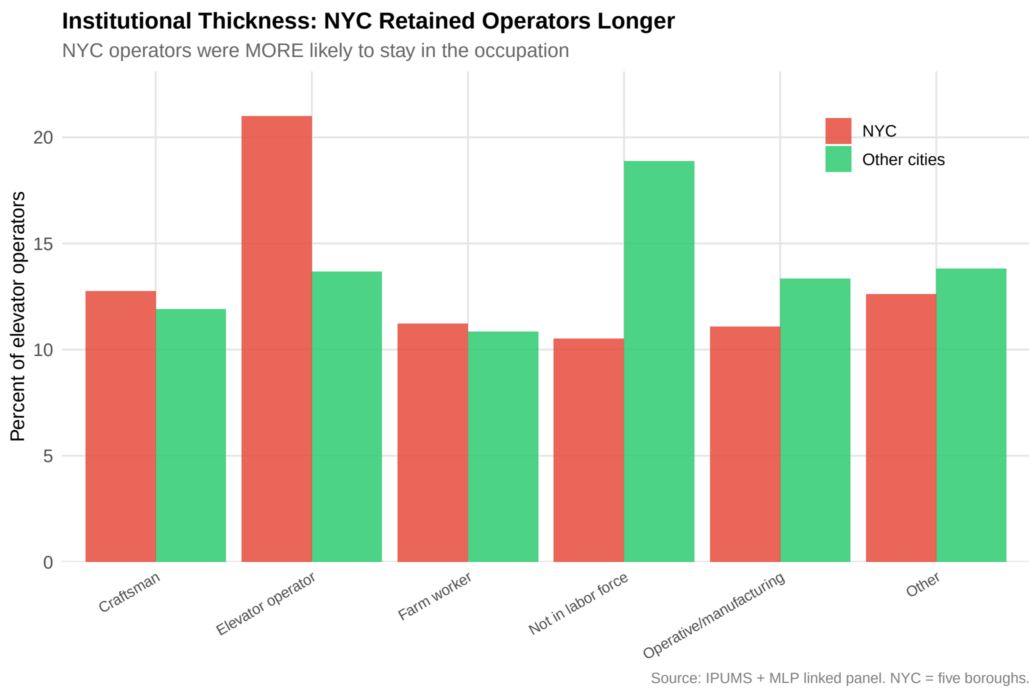


**Figure 13:** NYC vs. Non-NYC: Displacement Outcomes for 1940 Elevator Operators

Source: IPUMS + MLP v2.0 linked panel. NYC identified by COUNTYICP borough codes. NYC: N = 11,377. Non-NYC: N = 27,185.

Figure 13 and Section 6.5 compare outcomes for NYC and non-NYC operators. NYC operators had a 79% exit rate compared with 86% elsewhere—a seven-percentage-point gap consistent with institutional protection, which the regression confirms: the NYC indicator is positive and significant for persistence (+0.065, $p < 0.01$). For OCCSCORE changes, the unconditional descriptive means show NYC operators at +0.2 versus −1.4 for non-NYC; however, once controls are included, the regression coefficient on NYC is negative (−0.469, $p < 0.01$), reflecting that NYC operators who *did* exit tended to move to lower-prestige destinations than observably similar non-NYC exiters—consistent with Manhattan's higher concentration of Black operators, who faced more constrained destination options.

Within New York City, the five boroughs showed meaningful variation (Figure 14). Manhattan—the densest elevator market and the center of the commercial real estate industry—employed the most operators but had a 79% exit rate and the worst OCCSCORE outcomes (mean change −0.4). Manhattan's workforce was 29% Black, far higher than other boroughs (3–8%). Brooklyn had the lowest exit rate (77.5%) and positive OCCSCORE gains for exiters. The Bronx and Queens, with smaller operator pools and fewer Black workers, showed the best outcomes for those who left.

Table 7: NYC vs.~Non-NYC: Institutional Thickness and Displacement

| | 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
SE clustered by state.

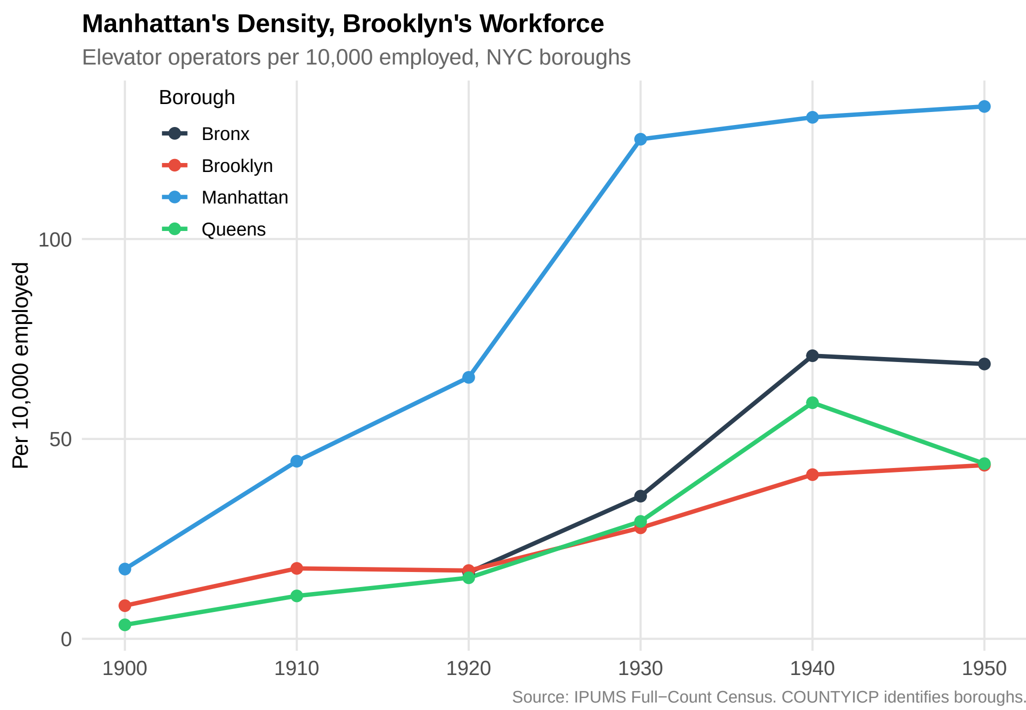


**Figure 14:** Elevator Operators Across New York City Boroughs, 1900–1950
Source: IPUMS Full-Count Census. Boroughs identified by COUNTYICP codes.

## 7. Heterogeneity in Displacement

The aggregate patterns above suggest that displacement was far from uniform. We systematically examine heterogeneity along three dimensions—race, sex, and geography—using

Table 8: 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
SE clustered by state.

individual-level regressions.

Section 7 presents results from three specifications, each interacting the elevator operator indicator with a demographic characteristic. The dependent variable is whether the worker remained in the same occupation from 1940 to 1950 (persistence). Column (1) interacts operator status with race; Column (2) with sex; Column (3) with NYC residence.

The results sharpen the descriptive patterns. The interaction between elevator operator status and race is large and significant ($-0.057$, $p < 0.01$): Black elevator operators were substantially less likely to persist than white operators, even after controlling for age, geography, and other observables. This differential persistence—combined with the destination channeling documented in Section 6—means that displacement's costs fell disproportionately on Black workers along two margins: they were more likely to be displaced, and they ended up in worse occupations when they were.

The sex interaction is also significant and large ($+0.077$, $p < 0.01$): female elevator operators were substantially more likely to persist than male operators, consistent with the selection pattern. Women entering the occupation in the 1940s may have had fewer

Table 9: 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. | 483773 | 483773 | 483773 | 483773 |
| R2 | 0.052 | 0.054 | 0.201 | 0.201 |

* p <0.1, ** p <0.05, *** p <0.01
Weights trimmed at 99th percentile.

outside options than men, particularly in the immediate postwar labor market when returning veterans reclaimed many positions. NYC residence strongly predicted staying (+0.073, $p < 0.01$), confirming the institutional thickness mechanism.

## 8. Robustness and Sensitivity

### 8.1 Inverse Probability Weighting

The MLP linkage rate of 47% raises concerns about selection bias. We estimate a logit model of linkage probability as a function of age, race, sex, nativity, marital status, and NYC residence, then weight all analyses by the inverse of predicted linkage probability (trimmed at the 99th percentile). Section 8.1 compares unweighted and IPW-reweighted estimates for our main specifications. The persistence and interstate-move coefficients are substantively unchanged under reweighting. The OCCSCORE change estimate, however, shifts from $-0.132$ (insignificant) to $-0.342$ ($p < 0.01$), suggesting that the unweighted estimate understates the occupational prestige penalty associated with being an elevator operator. This discrepancy arises because IPW upweights younger and female workers—groups more likely to experience downward occupational transitions—who are underrepresented in the linked sample. We interpret this as evidence that, if anything, our unweighted estimates are conservative regarding the prestige costs of displacement.

### 8.2 OCC1950 Cleaning Sensitivity

Our baseline rates use a cleaned employed denominator that excludes OCC1950 special codes (0, 979–999). To verify that our conclusions are robust to this choice, we recompute all per-10,000 rates using the uncleaned denominator. The qualitative pattern is identical—the arc still peaks in 1940 and collapses after 1960—but levels are 8–14% lower, as expected from the inflated denominator. All figures and tables in the main text use the cleaned denominator.

### 8.3 Comparison Group Robustness

Our displacement regressions compare elevator operators with five other building service occupations (janitors, porters, guards, charwomen/cleaners, and housekeepers). This broad comparison group is appropriate because all six occupations shared similar skill requirements and worked in the same buildings, but elevator operation was uniquely vulnerable to automation. The replication code (04_robustness.R) includes alternative specifications restricting the comparison group to narrower subsets; these alternative specifications are available for inspection in the replication archive.

### 8.4 Synthetic Control Method

As an alternative approach, we implement a synthetic control method (SCM) following Abadie et al. (2010) to compare New York State's elevator operator trajectory with a synthetic counterfactual constructed from comparison states with large urban centers. The pre-1940 match uses elevator operators per 10,000 population. After 1940, New York diverges from its synthetic control, consistent with NYC's institutional protections slowing the pace of automation relative to other large cities. Placebo tests (assigning treatment to each donor state) provide supporting evidence that the New York gap is unusual. Details are in Section D.

## 9. Discussion

The elevator operator case offers three lessons for understanding how automation displaces workers.

**Lesson 1: Technology adoption is institutional, not technological.** The automatic elevator was available by 1900. The occupation it replaced did not begin declining until the 1940s and did not effectively disappear until the 1970s. Forty to seventy years of coexistence between a technology and the occupation it would eventually eliminate is not an anomaly in the history of automation (Mokyr, 1992), but it is difficult to reconcile with models that treat displacement as a relatively rapid consequence of technological availability (Acemoglu and Restrepo, 2020). The elevator case suggests that the relevant question is not "when was the technology available?" but "when did the institutional, economic, and cultural barriers to adoption erode?"

In New York City, union contracts, building codes, and tenant preferences coincided with slower occupational decline relative to less-organized markets. We cannot cleanly identify the causal effect of these institutions—NYC differs from other cities along many dimensions (building stock, density, demographics, immigration)—but the pattern is consistent with institutional barriers delaying automation. The newspaper evidence shows that public discourse shifted against elevator operators in the late 1940s, while the institutions that protected them persisted for another generation.

**Lesson 2: Occupational exit is demographically stratified.** The 84% exit rate between 1940 and 1950 is not exceptional: other building service workers—janitors, porters, and guards, none of whom faced automation—exited at nearly identical rates (81–84%). The 1940s were a period of extraordinary labor market churn, driven by wartime mobilization and postwar reconversion, that reshuffled workers across occupations regardless of automation pressure. What distinguishes elevator operators from comparison workers is not the *rate* of exit but the *destinations*: where displaced workers ended up depended sharply on who they were.

Where displaced workers ended up depended on who they were. White operators—who had access to craft and clerical positions through established networks and lower discriminatory barriers—experienced genuine upward mobility on average. Black operators, facing pervasive employment discrimination in the 1940s labor market, were channeled into other low-status service positions. This finding resonates with contemporary evidence on automation's distributional consequences (Acemoglu and Restrepo, 2020; Autor, 2024) and with the historical literature on racial segmentation in labor markets (Sundstrom, 1994).

**Lesson 3: Declining occupations attract disadvantaged workers.** The entry analysis reveals a pattern that may characterize occupations in late-stage decline. Even as 84% of 1940 operators exited by 1950, the occupation barely shrank because 36,700 new workers entered. These entrants were disproportionately women (30% vs. 14% of exiters) and overwhelmingly drawn from outside the labor force (40%). For these workers, elevator operation represented a step up. The occupation was simultaneously being abandoned by its most advantaged workers and adopted by its most disadvantaged—a dynamic that accelerated both its demographic transformation and its cultural devaluation.

The newspaper evidence supports this interpretation: by the 1950s, the occupation was no longer described as a respectable position but as something held by people who had no better alternatives. This self-reinforcing mechanism—where exit of advantaged workers lowers status, which drives further exit and attracts more disadvantaged entrants—may be a general feature of occupational decline that deserves further study in the context of contemporary automation.

### 9.1 Limitations

Several limitations warrant acknowledgment. First, the linked panel covers only one decade (1940–1950), which coincides with the plateau phase rather than the collapse, and which includes World War II and its aftermath—a period of massive labor market disruption that affected all occupations, not only those facing automation. We cannot fully separate automation-driven transitions from war-related reallocation, though the comparison with other building service workers (who experienced similar exit rates but different destinations) helps isolate occupation-specific patterns. We cannot directly observe individual-level displacement during the 1960s and 1970s, when the occupation actually went extinct. Second, the MLP linkage rate of 47% introduces potential selection bias, though our IPW analysis suggests this is not driving results. Third, the newspaper analysis is limited to strategically sampled years and does not provide a continuous time series; our lead/lag claims about discourse preceding occupational decline should be understood as suggestive patterns, not formally tested temporal relationships. The keyword-based classification is deterministic and reproducible but necessarily involves researcher degrees of freedom in keyword selection; hand-coded validation on a random sample provides partial assurance of accuracy (see Section B). Fourth, OCCSCORE is a crude measure of occupational quality that may not capture important dimensions of job satisfaction, stability, or working conditions. Fifth, we cannot distinguish voluntary exits (workers who chose to leave for better opportunities) from involuntary displacement (workers who were fired when buildings automated); the similar exit rates across all building service occupations (81–84%) suggest that the 1940s were a period of high occupational mobility generally, making it difficult to attribute any individual exit to automation. Sixth, our regression standard errors are clustered at the state level (49 clusters), which is appropriate for national-level inference but may not fully account for within-state correlation in outcomes, particularly for geographic comparisons such as NYC versus non-NYC; future work could explore metro-level clustering or wild cluster bootstrap to assess sensitivity of inference. Seventh, wartime capital constraints—shortages of steel, electronics, and construction materials during World War II—may have independently delayed elevator automation during the 1940s plateau, creating an alternative explanation for the institutional-delay patterns that is distinct from union and regulatory barriers. Finally, the elevator operator case has features—urban concentration, union organization, regulatory barriers, and safety concerns—that may limit generalizability to other occupations. The institutional-delay finding likely generalizes to occupations where unions or regulations create adoption barriers, but occupations without such protections may experience faster displacement.

## 10. Conclusion

The elevator operator is one of the clearest cases in American history of an occupation fully eliminated by a specific, identifiable technology. Its lifecycle—rise alongside available automation, prolonged institutional coexistence, discursive delegitimation, demographic transformation, and eventual extinction—offers a complete case study in how technology displaces labor. The process took seventy years.

The newspaper record documents how the cultural meaning of the occupation changed. Elevator operators went from being treated as trusted figures in urban life to being framed as unnecessary expenses, and this discursive shift is visible in the data before the occupation's quantitative collapse. The apparent sequence—technology precedes discourse, discourse precedes institutional change, institutional change precedes displacement—is suggestive of a general pattern, though establishing causality or precise temporal ordering requires evidence beyond what a single case study with sparse temporal sampling can provide.

The distributional findings are sobering. When the occupation finally did contract, the costs were borne unequally. White workers, with better access to alternative employment, experienced genuine mobility. Black workers, facing a segregated labor market, were channeled into positions no better—and often worse—than the one they lost. The feminization of the occupation in its final years suggests that declining occupations attract exactly the workers with the fewest alternatives, creating a feedback loop that accelerates both the occupation's decline in status and its eventual elimination.

As artificial intelligence technologies raise new questions about which occupations will survive, the elevator operator case provides a framework for thinking about what comes next. Technology determines what *can* be automated. Institutions, culture, and politics determine what *will* be automated, and when. The distributional consequences—who bears the costs of displacement—depend on the same forces of discrimination and segmentation that have always structured the American labor market. If the past is any guide, the workers displaced by AI will not all end up in the same place. Where they land will depend less on the technology than on who they are.

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## A. OCC1950 Cleaning Protocol

The Census Bureau's OCC1950 harmonized occupation code includes several special codes for individuals who are not currently employed in a classifiable occupation. These codes appear in varying proportions across census years:

- Code 0: Not in labor force / no occupation reported
- Code 979: Not yet classified (prevalent in 1920; absent in 1940)
- Codes 980–987: Experienced worker with no current occupation

- Code 990: New worker (1940 census only)
- Code 995: Unpaid family worker
- Code 999: Occupation not reported (543,000 in 1920; 1.45 million in 1940)

Including these individuals in the employed denominator inflates the base and understates per-capita occupation rates by 8–14% depending on the census year. Our baseline analysis excludes all special codes from the denominator. We verify that this cleaning does not alter qualitative conclusions through a sensitivity analysis comparing cleaned and uncleaned rates across all census years.

## B. American Stories Methodology

### B.1 Article Retrieval

We use a two-stage filtering process to identify building-elevator articles from the American Stories corpus (Dell et al., 2023) while minimizing contamination from grain elevator references.

**Stage 1 (Broad Match):** We apply an OCR-tolerant regular expression to all article text in each sampled year. The pattern `[ec]l[ec]vat[oa]r` captures common OCR substitution errors in historical newspaper digitization, where "e" and "c" are frequently confused, as are "o" and "a." This yields 71,894 articles across 14 sampled years.

**Stage 2 (Disambiguation):** Articles matching the broad pattern are classified as:

- **KEEP:** Contains high-signal phrases unambiguously related to building elevators ("elevator operator," "elevator boy," "elevator girl," "automatic elevator," "self-service elevator," "push-button elevator," "elevator strike," "elevator shaft," "Otis elevator")
- **GRAIN:** Contains agricultural context ("bushel," "grain elevator," "wheat," "harvest," "terminal elevator," "country elevator") without any high-signal building elevator phrases
- **AMBIGUOUS:** Matches broad pattern but neither high-signal nor grain context

GRAIN articles (723 across all sampled years) are excluded. The remaining 71,171 KEEP and AMBIGUOUS articles are retained for thematic classification.

### B.2 Thematic Classification

We classify retained building-elevator articles into five thematic categories using a deterministic keyword dictionary. Each article is assigned to the first matching category in priority order:

1. **STRIKE:** Keywords: "strike," "walkout," "picket," "stopped work," "walk out"
2. **AUTOMATION:** Keywords: "automatic elevator," "push-button," "self-service elevator," "operatorless," "automatic service," "push button"
3. **LABOR:** Keywords: "union," "wage," "working condition," "organize," "AFL," "CIO," "Local 32," "building service employee"
4. **ACCIDENT:** Keywords: "accident," "injur," "kill," "fell," "crush," "death," "trap," "plunge"
5. **CONSTRUCTION:** Keywords: "new building," "under construction," "install," "equip," "stories high," "story building"

Articles matching none of these keyword sets are classified as OTHER. This deterministic approach is fully reproducible and transparent—no model-based classification is involved. The keyword dictionary was developed iteratively by reading samples of matched articles and identifying high-signal terms for each category.

Of the 71,171 retained articles, 7,458 are classified into one of the five thematic categories. The majority of retained articles (63,713) fall into OTHER, reflecting the many incidental mentions of elevators in news stories about buildings, crimes, and daily life.

### B.3 Corpus Normalization

The American Stories corpus varies in coverage across years due to the irregular digitization of the underlying Chronicling America collection. To ensure that temporal trends in elevator coverage reflect genuine discourse changes rather than corpus composition, we compute total article counts for each of the 14 sampled years by streaming through every newspaper scan in the year's archive. We then express elevator coverage as a rate per 10,000 total corpus articles.

### B.4 Geographic Identification

We identify the publication city for each article by parsing the `newspaper_name` field in the American Stories metadata. This field typically follows the format "Newspaper Title. [volume] (City, State) YYYY-YYYY." We extract the parenthetical location using regular expressions and supplement with a manual lookup table for newspapers whose metadata lacks the location pattern (e.g., "Evening star." → Washington, D.C.). We successfully resolve geography for 90% of matched articles.

### B.5 Validation

To assess the accuracy of the keyword classifier, we hand-code a random sample of 100 articles drawn from the thematically classified set (excluding OTHER). For each sampled article, we read the headline and first 200 words and assign a category based on the primary subject matter. We then compare the hand-coded category to the keyword-assigned category.

Of the 100 sampled articles, 29 received the same category from both the keyword classifier and hand-coding (overall precision: 29%). By category: AUTOMATION had the highest precision (4 of 5 correctly classified, 80%), followed by ACCIDENT (24 of 37, 65%). CONSTRUCTION (0 of 26) and LABOR (0 of 27) had zero precision—these broad keywords ("build," "construct," "wage," "employ") almost always captured articles mentioning elevators incidentally rather than as the primary subject. STRIKE had low precision (1 of 5, 20%). The majority of mismatches (63 of 71) involved articles that the keyword classifier assigned to a thematic category but that hand-coders judged to be OTHER—incidental mentions of elevators in stories primarily about other topics. These results underscore that the keyword classifier captures a mix of genuinely thematic articles and incidental elevator mentions, and that absolute article counts should be interpreted with caution. The temporal and geographic *patterns*—which are the focus of our analysis—are less sensitive to uniform false positive rates across years.

## C. County-to-Metro Crosswalk

We identify metropolitan areas using IPUMS COUNTYICP codes. The crosswalk maps each county to its principal city, covering the 23 largest metropolitan areas by elevator operator count. New York City boroughs are identified separately: Manhattan (610), Brooklyn (470), Queens (810), Bronx (050), and Staten Island (850). The full crosswalk is available in the replication code.

## D. Synthetic Control Method

We implement a synthetic control method following Abadie et al. (2010) to estimate the counterfactual trajectory of elevator operator employment in New York State (home to the densest elevator market and the strongest institutional protections). The donor pool consists of comparison states with large urban centers (Illinois, Pennsylvania, Massachusetts, California, Michigan, Ohio, New Jersey, D.C., Maryland), measured in elevator operators per 10,000 population. Pre-treatment covariates include 1900–1930 rate levels. The treatment period begins in 1940.

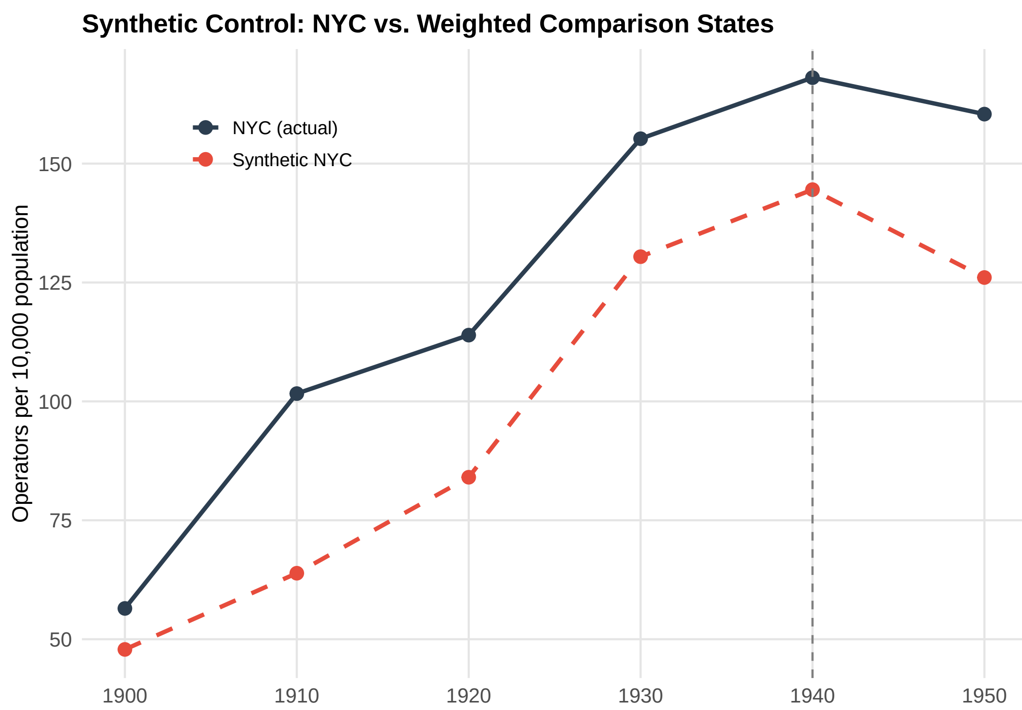


**Figure 15:** Synthetic Control Method: New York State vs. Synthetic Comparison

Treated unit: New York State (STATEFIP = 36). Donor pool: 9 comparison states with major urban centers. Outcome: elevator operators per 10,000 population. Pre-treatment: 1900–1930. Dashed vertical line marks treatment onset (1940).

The synthetic New York shows a different trajectory from actual New York after 1940, consistent with the institutional thickness story—NYC's operator market evolved differently from what the comparison states' trends would predict. Permutation inference (placebo tests assigning treatment to each donor state) provides supporting evidence.

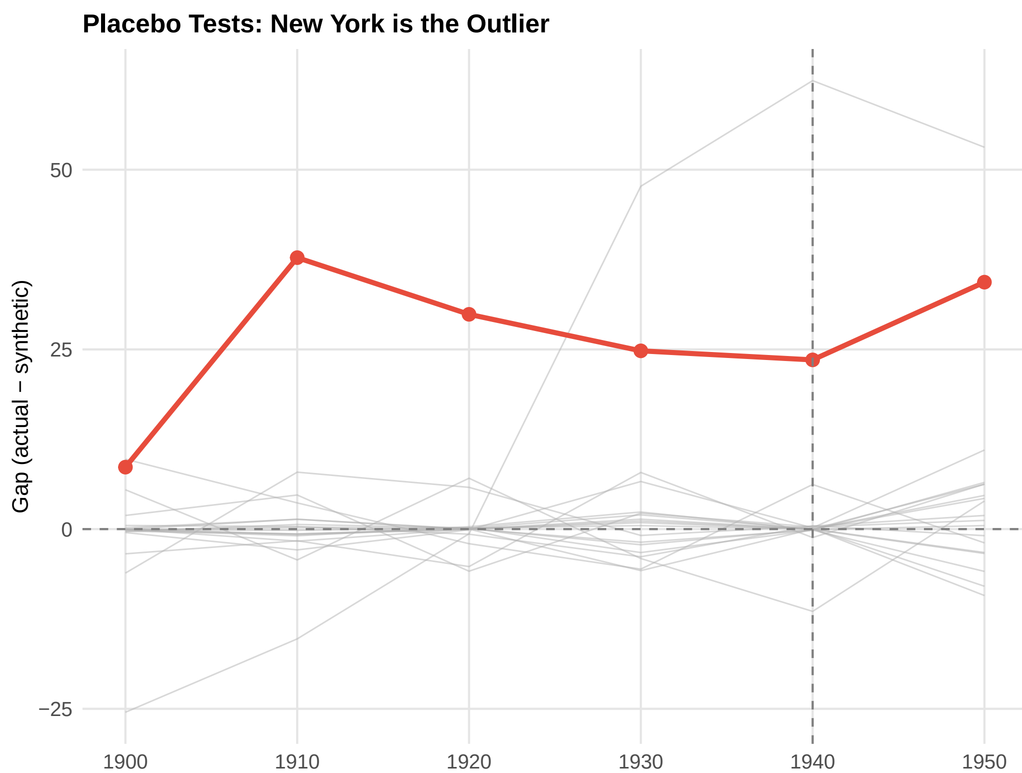


**Figure 16:** Placebo Tests: New York vs. Donor States

Each line shows the gap (actual minus synthetic) for one state. New York's gap (dark line) diverges after 1940. Dashed vertical line marks treatment onset.


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**Project Repository:** https://github.com/SocialCatalystLab/ape-papers