The Economic Effects of Place: Evidence from Child Migration during the Orphan Train Movement

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Abstract

This project evaluates the lifetime and intergenerational impact of place on socioeconomic outcomes stemming from Orphan Train Movement, the relocation of approximately 300,000 orphaned and surrendered children in New York City to families across the U.S. from 1853 to 1929. Utilizing variation in placement locations relative to an individual's entry into an orphanage, we estimate the effect of place, both geographically and characteristically, on a broad set of measures for Orphan Train riders and their descendants. To accomplish this, we develop a novel dataset by digitizing information from historical ledgers, research documents, and state-level censuses during this period to identify children in participating orphanages. This data is linked to complete-count decennial U.S. Censuses from 1850 to 1940. We find that riders who were placed in more urban, wealthy, and populous counties have higher lifetime occupational income scores and fewer children, and that children of riders see similar effects, indicating that place has intergenerational impacts.

JEL classifications: N31, N32, I31, J13, R23

Keywords: Intergenerational transmission, Migration, Child welfare

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1 Introduction

Social scientists are increasingly concerned with how the characteristics of our communities shape persistent and intergenerational socioeconomic outcomes. Recent research has identified institutional factors correlated with intergenerational mobility, including lower residential segregation, reduced income inequality, stronger social capital, more excellent family stability, and higher-quality schools (Chetty, Hendren, Kline, & Saez, 2014). In addition, studies suggest that the effects are larger for younger children due to prolonged exposure to better communities (Chetty, Hendren, & Katz, 2016). Children also see prolonged benefits from exposure to stable mentorship and community support in high-opportunity areas (Chetty & Hendren, 2018; Chyn, 2018).

However, there are key gaps in the existing literature studying the persistent effects of place. First, due to a lack of quasi-experimental variation, some evidence describing how place-based factors drive intergenerational mobility is descriptive (as in Chetty et al. (2014)). Existing causal evidence is limited in geographical scope and focuses on moves across neighborhoods within a metropolitan area (Chetty et al., 2016; Chyn, 2018; Ludwig et al., 2013). Second, many large-scale experiments and public programs that induce people to move to better places occurred recently and are unable to estimate the effects on the children of Orphan Train Riders.

We fill this gap in the literature by causally examining the effects of the Orphan Train movement, the first large-scale social welfare program serving disadvantaged children in the United States from 1853 to 1929. The Orphan Train facilitated the movement of impoverished children (referred to as "riders") from New York City to counties throughout the United States. Importantly, due to the institutional nature of the Orphan Train movement, the characteristics of the county where a child was placed were orthogonal to child characteristics. Studying this historical event enables us to examine two key additions to the existing literature on place's persistent effects: the effect of place-based characteristics on socioeconomic outcomes throughout the United States and the intergenerational impacts of

place among the children of individuals relocated as part of the Orphan Train movement.

To do this, we combine archival data from historical documents maintained by organizations involved in the Orphan Train with a longitudinally linked panel of Census data from the Census Tree project. Using these combined data, we are able to determine the county where a rider was placed and long-run socioeconomic outcomes for both riders and their children.

A key institutional feature of the Orphan Train movement is that once a child met a minimal threshold of physical and mental health, they were eligible to be an Orphan Train rider. As a result of high demand for children outside of New York City, children were being sent west on trains frequently, and orphanages did not take into account child characteristics when deciding where a child was placed (Kidder, 2003). Therefore, conditional on being a rider, the county where a child was placed is quasi-random, and we can determine how place-based institutions affect long-term outcomes.

We estimate the role of place-based institutional factors in each county where an orphan was placed by calculating the literacy rate, urban percentage, average land value, and population in the census year prior to a child's placement in that county. We then define treatment as being placed in a county that is above the national median for each of these characteristics separately.

We find that riders placed in above-median counties with respect to urbanization, property value, and population had higher occupational income scores, a benefit that extended to their children, indicating intergenerational persistence. Location also influenced family formation, with riders in above-median counties having fewer children, a trend that similarly persisted into the next generation.

In addition to our contributions to the Moving to Opportunity literature, our work also advances the forced relocation literature by examining the largest child migration event in the United States. Prior studies rely on variation from war, natural disasters, or policies destroying housing (Becker & Ferrara, 2019; Becker, Grosfeld, Grosjean, Voigtländer, &

Zhuravskaya, 2020; Bryan & Morten, 2019; Chyn, 2018; Lagakos, 2020; Moser, Voena, & Waldinger, 2014; Nakamura, Sigurdsson, & Steinsson, 2022; Sacerdote, 2012; Sarvimäki, Uusitalo, & Jäntti, 2022; Ward, 2022). We provide the first quasi-experimental long-run and intergenerational evidence of the persistent effects of one of the first large welfare programs in US history, which resulted in the forced relocation of approximately 300,000 children from New York City to counties across the United States.

2 Background

2.1 History of the Orphan Train Movement

During the early to mid-1800s, New York City faced substantial constraints regarding the city's infrastructure due to rapid increases in population. This population shock came from an influx of Irish, German, and Italian immigration, as well as rural migration to industrial urban centers. The increase in New York City's population combined with dangerous working conditions, lack of social welfare, alcoholism, and poverty led to a direct increase in the number of orphaned, surrendered, or displaced children. Many of these children had no additional family or resources in the nearby community (O'Connor, 2004).

Many public institutions were inadequately prepared for the influx of people, including existing child welfare programs. The public child welfare system (i.e. the foster care system), as it exists today, did not exist during the 19th century. Most child welfare programs were provided by religious or charitable organizations at the local level. Children were sometimes able to serve in apprenticeships, exchanging labor for food and shelter. However, the number of orphaned children far outweighed the number of economic opportunities in New York City. This left many children without adequate shelter, and no eisting charitable welfare programs could find a suitable setting for these children.

To solve this problem, Charles Brace and the Children's Aid Society, the largest charitable organization serving children at that time, began the Orphan Train Movement. The

purpose of the program was to place orphaned children in an environment that could serve their needs (Kidder, 2003). This was done through allocating orphaned, surrendered, or displaced (henceforth orphaned) children to families in the expanding western portion of the United States. A significant number of families in the western US were in need of or desired additional children due to the difficulties and dangers of childbirth and the need for additional agricultural labor. The Children's Aid Society served as an intermediary to establish an equilibrium, by removing the excess supply of orphaned children in New York City and moving them to meet the excess demand for children elsewhere.

The program took place from the 1850s to the 1920s, serving approximately 250,000 to 350,000 children. As shown in Figure 1, most riders were placed in upstate New York or the Midwest. This radical program has been met with mixed reactions, both at the time and in reflection of the event (Cook, 2017). However, the comprehensive quantitative effects for the individuals involved in the Orphan Train Movement have yet to be fully understood.

2.2 Potential Mechanisms

Recent research has provided several theoretical predictions on how location can affect long-run and intergenerational outcomes. Chetty et al. (2016) propose a model to explain their findings that younger children benefit more significantly from moving to better neighborhoods due to prolonged exposure to advantageous environments. This model balances the benefits of accessing better places, such as higher quality schools, safer communities, and stronger job markets, with the disruption costs associated with relocating. The positive impact of childhood exposure underscores the importance of early-life environment in shaping economic trajectories over time. These exposure effects likely have intergenerational effects, as children are very likely to live near their childhood home (Leopold, Geissler, & Pink, 2012; Sprung-Keyser, Hendren, Porter, et al., 2022).

Research also highlights the role of social structures and networks in geographic mobility and economic outcomes. Chyn (2018) examines the long-term effects of forced relocation

caused by housing demolitions and suggests that exposure to better social networks and role models in new neighborhoods drives positive outcomes. Similarly, Chetty and Hendren (2018) emphasize that the effects of childhood exposure to higher-opportunity neighborhoods increase with the duration of exposure. They attribute this to interactions with permanent residents who offer stability, mentorship, and community support, illustrating the transformative power of location on personal and economic development.

Geographic disparities also affect intergenerational mobility, and systemic factors perpetuate inequality. Buckles, Price, Ward, and Wilbert (2023) argue that assortative matching, where individuals tend to marry within similar economic strata, limits intergenerational mobility. Additionally, Chetty et al. (2014) identify structural factors in high-mobility areas, such as lower residential segregation, reduced income inequality, stronger social capital, greater family stability, and better schools, as key drivers of upward mobility. These findings inform our treatment selection, as we define treatment as being placed in a county that is above median on one of several dimensions, including literacy (proxy for education), property values (proxy for wealth), population (proxy for labor market size), and percent urban.

Based on previous findings, we expect Orphan Train riders placed in above-median counties to see improved labor market outcomes on average. Due the intergenerational persistence of location, we expect these effects to persist among children of riders. Improved labor market outcomes also imply lower fertility among riders and their children, as implied by the negative relationship between income and fertility (Dribe, Oris, & Pozzi, 2014; Jones & Tertilt, 2008).

3 Data

To examine the long-run and intergenerational effects of place, we combine newly digitized data on orphans involved in the Orphan Train movement with linked U.S. census records spanning 1850-1940. This process involves three steps, extracting orphan data, link-

ing orphan data to the census, and determining which of the children in the data participated in the movement.

3.1 Orphan Data

The exact number of Orphan Train riders is not known.[1] While organizations in other large eastern United States cities participated in the movement, most of the children were placed by organizations in New York City. We focus on these institutions since they transported the largest number of children over the longest time period. According to the National Orphan Train Complex, the four largest participating orphanages in New York City were the Children's Aid Society (CAS), the New York Foundling Hospital (NYFH), the New York Juvenile Asylum (NYJA), and the American Female Guardian Society (AFGS). We collect data from three of the four prominent orphanages in New York City that participated in the Orphan Train movement and used placement methods compatible with our identification strategy: CAS, NYJA, and AFGS.[2]

We gather data on children from these orphanages using a series of ledgers, state-level censuses, and research documents. The data are in two forms: digital scans or physical copies (See Figures A.3, A.4, and A.5 for examples of the records). To identify the correct individuals in the census, we digitize and extract the information from each source using a mixture of text scraping and manual input. From the state-level censuses, we extract first and last name, sex, gender, and age. From the ledgers and research documents, we find placement date, placement location, placing organization, and their surname.

[1]The Orphan Train movement involved numerous agencies without the direct oversight of a governing body over the span of 76 years. Documentation of the children varied across both time and orginizations making constructing a representative sample of children difficult. Estimates on the total number of riders vary from historical sources. Our best understanding is that the total number of participating children that in the program is between 250,000 and 350,000.

[2]NYFH had an important feature in their placing process that violates our assumption for quasi-random variation in placement location. NYFH would require prospective families to be approved prior to placement by local church officials. During this process, families would be able to request the types of children they were interested in housing. Since we cannot observe the entire set of characteristics that were possible to select from, we cannot test if different types of children were systematically placed to different locations. A detailed discussion of our identification strategy is presented in Section 4.1.

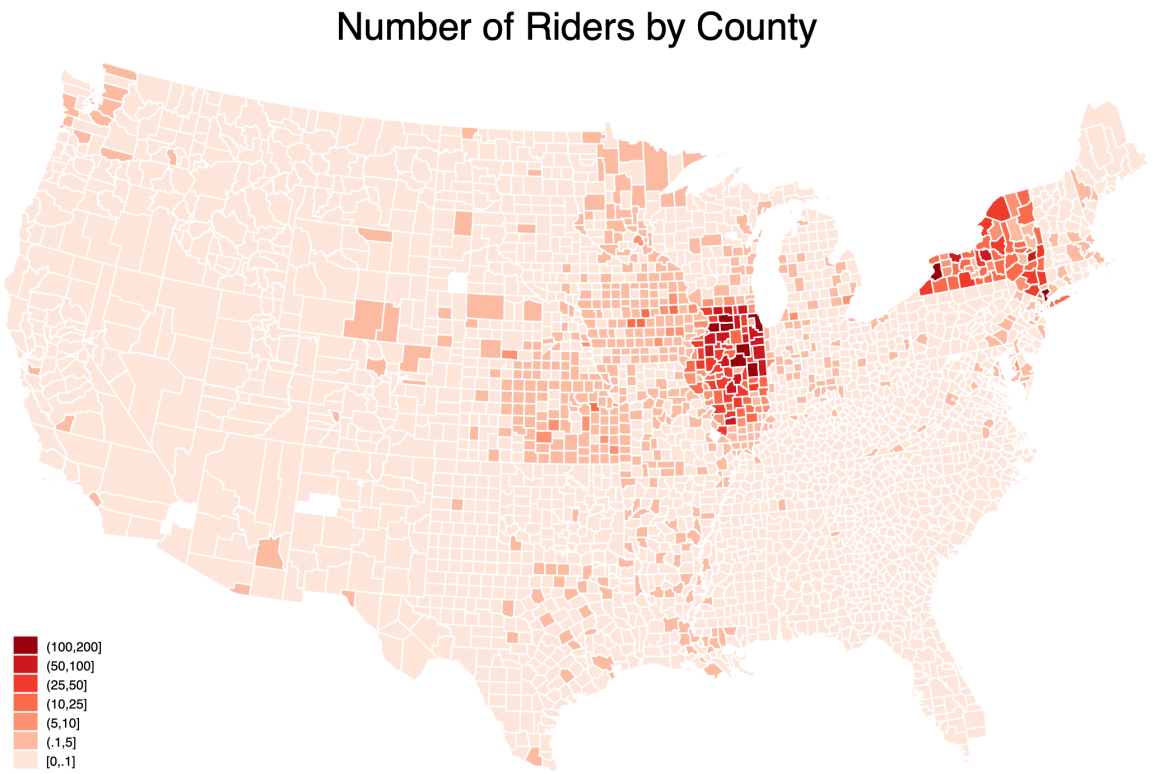


Figure 1: Distribution of Riders by County

The National Orphan Train Complex (NOTC) provides a valuable data source through its research documents. Unlike census or administrative records, these documents are compiled from historical research and ancestry requests. Because the individuals in NOTC's research are descendants of riders — who may not represent all riders — we categorize them as a separate entity. However, these riders originally came from various orphanages, including the three that we identify through other sources. This distinction ensures clarity in data interpretation and prevents potential bias in subsequent analyses.[3]. These research documents are extremely valuable as they help fill in the sample with riders both outside of and within the three institutions that our primary data sources failed to cover.

[3]Riders that are identified from NOTC and one of the three primary orphanages are dropped from the NOTC sample and kept in the other sample

3.2 Linking to Census Data

To link orphan records with the US Census, we use a probabilistic matching model which uses first and last name, year of birth, and state of residence[4]. We restrict the set of potential matches in the census to individuals with the same initials, who were born in the same decade as the orphan, and who are residing in the same state. Our matching process is repeated over 3 rounds, and in subsequent rounds, we relax some of these constraints. In each round of matching, the algorithm generates a match score (from 0 to 1) and we only keep unique matches that have a match score of 0.7 or greater[5]. This matching process results in about 70% of the orphans in our data being linked to the US Census[6]. Of the 15,000 orphans for whom we have data, we successfully linked 10,500 to at least one historical census.

3.2.1 Longitudinally Linked Census Data

To estimate the long-run and intergenerational effects of the Orphan Train Movement, we use a longitudinally linked Census dataset from 1850-1940, provided by the Census Tree Project [7]. This data allows us to follow individuals for up to 90 years and enables us to examine labor market outcomes and migration.

A useful feature of these data is that it follows both individuals and households over time. We use this feature to create an intergenerational sample of the children of the Orphan Train riders. To do this, we locate the households in the Census where riders were household head or spouse of the household head and aged 35-45. We then locate the children of the household head in these households, who were the children of our riders. The longitudinally linked Census data enables us to follow these children to adulthood and estimate intergenerational effects.

[4]The specific Stata command used is reclink
[5]This matching method is closest to the process used in Abramitzky, Boustan, and Eriksson (2014)
[6]See Price et al. (2021) for a discussion of linkage rates
[7]see the Census Tree Project website for more information

3.3 Defining Orphan Train Riders

It is important to note that these data contain both riders and non-riders, and it is necessary to distinguish them to examine the effect of place. To define whether an orphan was a rider, we use an iterative process. First, we rely on whether our primary data sources identify them as a rider, as indicated by historical ledgers and research documents. Next, for the remaining children, we are unable to identify rider status from the state-level censuses where we observe them in an orphanage. For these data, we classify an orphaned child as a rider if we link to the child in the decennial census and they are living in a county with a family outside of New York County, the location of the Children's Aid Society, or any of the surrounding counties (Bronx County, Queens County, and Kings County). Our final estimation of riders is consistent with the estimated distribution of riders from the Children Aid Society (Figure 2), which shows that many riders were placed in New York and Illinois.

4 Methodology

An important feature of the Orphan Train Movement is the quasi-random placement of children across the United States. We find anecdotal evidence of this through annual reports of orphanages involved in the Orphan Train movement. According to these annual reports, orphanages were capacity constrained prior to the Orphan Train, and after the movement began: "very soon our anxieties were not to find homes for the children, but children for the homes."[8]

We implement a reduced-form analysis to measure the immediate and intergenerational effects on socioeconomic outcomes of the first large-scale child welfare event in the United States. We examine the causal effect of place on the same set of immediate and intergenerational socioeconomic outcomes by examining the differences in outcomes between riders who went to better or worse counties. Our estimates provide quantitative evidence of the

[8]From the 1856 New York Juvenile Asylum annual report, see Kidder (2003)

effects of the Orphan Train movement.

We utilize the differential timing in the orphaned status of riders as an instrument to determine the treatment status of a rider, where treatment in this specification refers to the location a rider is placed. Riders were chosen to be placed based on a type of first-in-first-out selection criteria with respect to the availability of the next train conditional on meeting the prerequisites for being a rider. If an orphaned child was eligible to be a rider, contingent on the orphanage's policy, then a child would be placed on the next available Orphan Train in the absence of being adopted locally or reunified with their original guardians. Therefore, the comparison of riders across locations would be predicated on the timing of orphaned status, which is independent of unobserved characteristics that may affect socioeconomic outcomes.

4.1 Better Places Analysis

To estimate the county-level effects of the Orphan Train movement, we first identify whether the county to which each rider was sent was above or below the median of several county characteristics, including population, urbanicity, literacy, and land values. These characteristics are indicative of whether a county has larger labor markets[9], higher average education, and more wealth, all factors that are correlated with greater economic opportunity (Chetty, 2016). We define treatment in our context as an indicator for being placed in a county that is above-median on each of these characteristics. We then estimate the following equation:

$$Y_{ico} = \tau T_i + X_i'\beta + \gamma_{co} + \epsilon_{ico} \tag{1}$$

where our equation (2) varies from equation (1) in that T_i is a county characteristic treatment variable. $T_i = 1$ if rider i was placed in a county with above-median treatment value,

[9]Since we are estimating over a large time period with multiple recessions and a changing economic landscape, we use population as an acycical measure of labor market size.

and 0 if placed in a county with below-median treatment value for four treatments: literacy, urbanization, land value, and population. X_i' are time-invariant demographic controls and γ_{co} represents census year by orphanage fixed-effects. The coefficient on treatment, τ, measures the effect of being placed in an above-median county.

5 Results

5.1 Does placement in a better place matter?

To estimate the local average treatment effect of place on socioeconomic outcomes, riders must be placed in locations not predicated on unobservable characteristics that may affect outcomes of interest and allows for the groups of riders across regions to be comparable. This requires that the sorting of riders to certain locations is done in a manner that is independent of these unobserved factors.

As discussed previously, the institutional nature of the Orphan Train Movement led to a quasi-random sorting of children across counties. We provide quantitative evidence that location assignment was quasi-random in Tables 1 and 2. Table 1 examines the balance across all census years in our sample for each of our treatment definitions. We do this by regressing treatment status for each of the four treatments on demographic characteristics including, gender, placement age, race, and immigrant status. We find largely no systematic differences between treatment and control groups for all definitions of treatment.

To verify this is the case, we follow Imbens and Rubin (2015), and calculate normalized difference statistics for each treatment-covariate pair in Table 2. The normalized difference statistic is a sample size invariant statistic that measures comparability between treatment and control groups, and statistics smaller than 1 in absolute value suggest comparability between groups, as is the case for all cells in Table 2.

Next, we examine the differences between riders who went to better and worse counties. Looking at average prima-age occupational income score in Panel A of Table 3, we find that

riders who were placed in populous, more urban counties had higher occupational income scores. Riders placed in these counties had income scores that were 1.30 and 0.94 points higher than their non-treated counterparts, respectively. This likely reflects the role that access to larger labor markets plays in upward mobility. In Panel B, children of riders placed in more urban and wealthy counties had higher occupational income scores (1.08 and 1.55 points, respectively), indicating intergenerational persistence of these effects.

Location also impacts family formation decisions as seen in Table 4, which estimates the effects of being in a better place on total number of children. In Panel A, riders placed in more urban, populous, and wealthier counties had 0.13 to 0.2 fewer children, on average. These effects persist into the second generation, as children of riders placed in these counties also had 0.21 to 0.29 fewer children.

5.2 Robustness

One potential concern is that the differences between better and worse counties are a result of differences across geographical regions. To examine this, we estimate a similar equation as before, but here treatment is an indicator for being in one of 5 Census regions: New England, East Midwest, West Midwest, South, and West.

Specifically, we define the empirical design as follows:

$$Y_{ico} = \sum_{j=1}^{5} \eta_j L_{ij} + X_i'\beta + \gamma_{co} + \epsilon_{ico} \tag{2}$$

indexed by individual i; census year c; orphanage o; and region j. Y_{ico} is our socioeconomic outcome of interest that covers occupational income score and number of children. L_{ij} denotes an indicator variable which takes a value of 1 for the the region j which individual i was sent to and 0 for all other j regions. The associated coefficients of interest are η_j, measuring the effect of the j region, relative to our omitted region (Mid-Atlantic, where New York City is located). The results of this exercise are in Table A.5

For our occupation income score regressions, we find that most regions are of a similar sign and magnitude in the first generation, with only the coefficient on West Midwest having statistical significance. In the second generation, all coefficients are negative and statistically insignificant, with the exception of New England, which is positive and statistically significant at the 10% level.

For our fertility regressions, in the first generation we find a positive result across all regions (that is statistically significant for all regions except West). In the second generation, the results are of varying magnitude and direction, ranging from -0.92 children (New England) to 1.08 children (South). Overall, our regional analysis assuages concerns that our main findings are not being driven by regional geographic differences.

5.3 Discussion

Our findings have several important implications. First, they underscore the critical role of place in shaping economic and demographic outcomes. Regional and county-level differences in economic opportunities can have lasting effects on both individuals and their descendants. Policies aimed at reducing place-based disparities in opportunity may be essential for improving long-term mobility outcomes.

Second, the intergenerational persistence of both labor market and fertility outcomes highlight the importance of addressing place-based inequalities early in life. The benefits of living in a better place extend beyond the first generation, implying that policies aimed at reducing place-based inequality may have returns that span multiple generations.

Lastly, the observed trade-off between economic opportunity and family size raises important questions about the interplay between socioeconomic mobility and demographic behaviors. Policies that help mitigate these trade-offs could promote both economic and demographic well-being.

6 Conclusion

We provide compelling evidence that location significantly impacts long-term and intergenerational socioeconomic outcomes. By leveraging the quasi-random placement of children in the Orphan Train Movement, we avoid selection bias and obtain causal estimates of the role of place in shaping individual trajectories. We find that riders placed in better counties have better occupational income and fewer children, and that these effects persist into the second generation

Our findings contribute to the Moving to Opportunity literature by exploring novel dimensions such as family formation, fertility, and intergenerational mobility. Additionally, this research advances the broader migration literature by examining a unique historical event involving one of the largest child relocation programs in US history. The program's quasi-random design and the diverse placements allow for meaningful insights into population differences across both regions and counties, enriching our understanding of the socioeconomic consequences of migration and place.

By highlighting the profound and enduring effects of location on individuals and their descendants, we underscore the critical importance of place in shaping life outcomes and inform contemporary policy discussions on migration, child welfare, and socioeconomic mobility.

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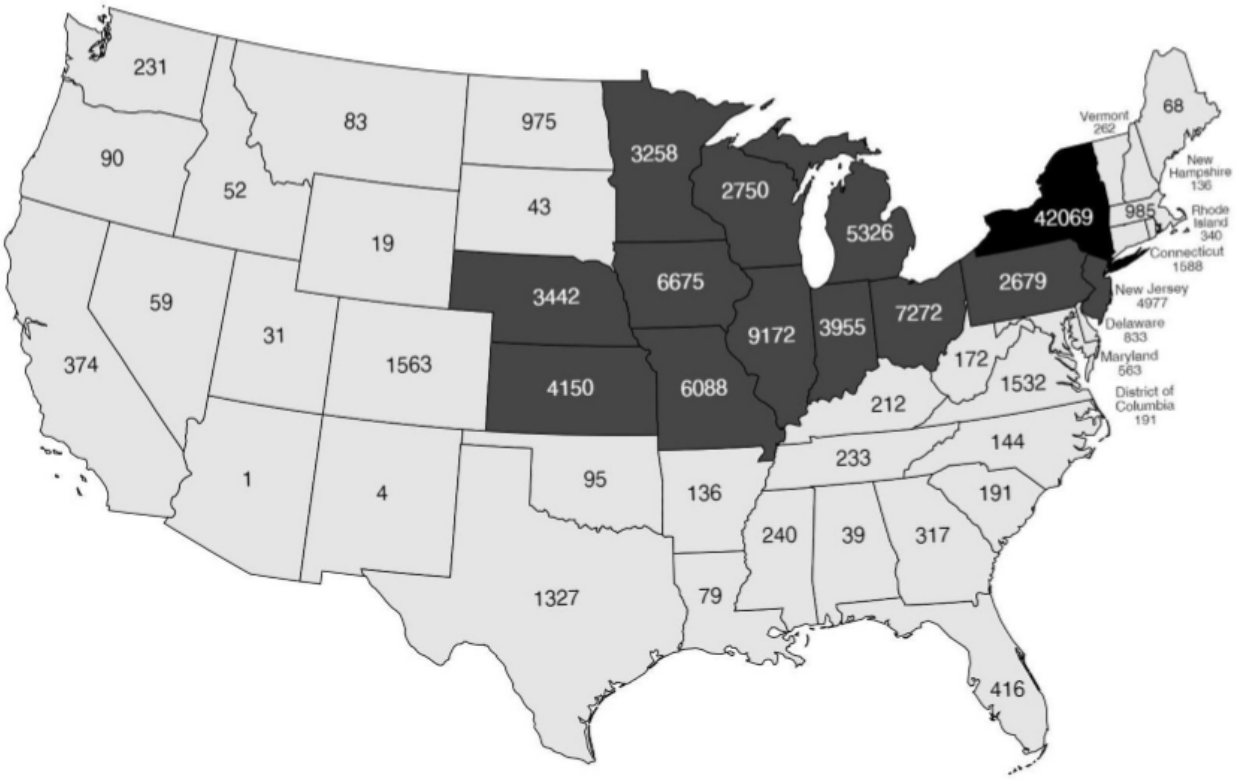
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Tables and Figures



Source: National Orphan Train Complex and CAS annual reports

Figure 2: Estimated Number of Child Placements Per State by the Children's Aid Society

VARIABLES	1850	1860	1870	1880	1900	1910	1920	1930
A. Literacy Treatment								
Female	0.157*	0.091	0.023	0.002	-0.006	0.001	-0.003	-0.008
	(0.070)	(0.048)	(0.025)	(0.023)	(0.016)	(0.020)	(0.021)	(0.024)
White	0.122	0.175	0.157	0.182*	0.124	0.232**	0.272**	0.250*
	(0.249)	(0.200)	(0.116)	(0.072)	(0.066)	(0.075)	(0.092)	(0.107)
Placement Age	0.001	0.003	0.007	0.006	-0.001	-0.002	-0.002	-0.003
	(0.012)	(0.007)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Native	0.157	-0.051	-0.011	-0.012	0.038	0.023	-0.007	-0.036
	(0.129)	(0.075)	(0.077)	(0.045)	(0.037)	(0.052)	(0.053)	(0.055)
B. Land Value Treatment								
Female	0.038	-0.001	-0.005	0.000	0.035**	0.040**	0.051**	0.040*
	(0.032)	(0.014)	(0.008)	(0.005)	(0.012)	(0.014)	(0.016)	(0.016)
White	0.008	0.028	0.026**	0.009	0.000	0.067	0.097	0.155*
	(0.011)	(0.016)	(0.009)	(0.019)	(0.038)	(0.048)	(0.067)	(0.060)
Placement Age	-0.000	-0.003	-0.001	-0.001	0.001	0.001	-0.001	-0.002
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Native	0.015	0.018*	-0.002	-0.006	0.004	0.032*	0.018	0.046**
	(0.010)	(0.007)	(0.012)	(0.008)	(0.013)	(0.014)	(0.017)	(0.014)
C. Urban Treatment								
Female	0.019	0.003	0.010	0.008	0.017	0.021	0.032*	0.021
	(0.025)	(0.010)	(0.008)	(0.005)	(0.009)	(0.011)	(0.013)	(0.013)
White	0.012	0.020	-0.014	0.022	-0.035	0.010	0.006	0.049
	(0.011)	(0.010)	(0.049)	(0.027)	(0.054)	(0.061)	(0.087)	(0.079)
Placement Age	-0.003	-0.003	-0.001	-0.001	-0.002*	-0.003**	-0.003*	-0.003*
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Native	0.012	0.015	-0.009	-0.050	-0.056	-0.063	-0.061	-0.096
	(0.009)	(0.009)	(0.012)	(0.034)	(0.038)	(0.052)	(0.049)	(0.072)
D. Population Treatment								
Female	0.019	-0.002	0.006	0.006	0.013	0.013	0.024	0.017
	(0.025)	(0.011)	(0.008)	(0.006)	(0.009)	(0.010)	(0.013)	(0.011)
White	0.012	0.030	0.032*	0.038*	0.041	0.098**	0.118**	0.116**
	(0.011)	(0.016)	(0.015)	(0.016)	(0.032)	(0.034)	(0.034)	(0.036)
Placement Age	-0.003	-0.005	-0.002*	-0.001	-0.002**	-0.004**	-0.003**	-0.004**
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Native	0.012	0.018	-0.008	-0.047	-0.055	-0.061	-0.060	-0.090
	(0.009)	(0.010)	(0.012)	(0.035)	(0.038)	(0.053)	(0.050)	(0.074)
Observations	205	604	1,515	2,498	3,368	2,743	2,203	1,804

Table shows the balance tests for each treatment. Each panel regresses treatment status on covariates for each census year. Treatment status is determined by being above median for each of the four variables as outlined in Section 4.1. Each row indicates a covariate being tested, while each column represents a specific census year. Orphanage controls are included. * $p < 0.05$, ** $p < 0.01$

Table 1: Balance Test of All Treatments and Rider Covariates

	Literacy	Land Value	Urban	Population
Female	0.022	0.136	0.020	0.046
White	0.347	0.018	0.465	0.168
Placement Age	0.227	0.085	0.463	0.240
Native	0.211	0.089	0.482	0.300

This table contains the absolute value of the estimated normalized difference statistics for each treatment and covariate combination. Treatments are represented in each column, while covariates are represented in each row. According to Imbens and Rubin (2015), a normalized difference statistic smaller than 1 in absolute value indicates that the treatment and control groups are comparable. See Imbens and Rubin (2015) for calculation details.

Table 2: Imbens Normalized Differences for County Treatment Groups

	Literacy	Urban	Land Value	Population
A. 1st Generation				
Avg. Occscore	-0.058	0.939**	0.771*	1.300***
	(0.296)	(0.359)	(0.396)	(0.381)
N	3,959	3,959	3,959	3,959
R-squared	0.394	0.392	0.393	0.394
B. 2nd Generation				
Avg. Occscore	-0.244	1.086**	1.548**	0.772
	(0.501)	(0.494)	(0.591)	(0.470)
N	3,144	3,144	3,144	3,144
R-squared	0.438	0.440	0.441	0.439

Each column is a separate regression for each of the four county-level treatments outlined in Section 4: literacy, urbanicity, average land value, and population. Panel A reports results of the effect of each treatment on average prime-age (25-54) occupation score for the 1st generation (Orphan Train riders). Panel B reports results of the effect of each treatment on average prime-age occupation score for the 2nd generation (children of riders). Demographic controls include gender, age, race, and immigrant status. Orphanage-census year fixed effects are included in all regressions. Standard errors are clustered at the orphanage-census year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Occupation Income Score Effects

	Literacy	Urban	Land Value	Population
A. 1st Generation				
Number of Children	-0.037	-0.154***	-0.130*	-0.204***
	(0.065)	(0.057)	(0.074)	(0.062)
N	5,238	5,238	5,238	5,238
R-squared	0.065	0.066	0.065	0.066
B. 2nd Generation				
Number of Children	0.033	-0.293***	-0.239***	-0.209***
	(0.059)	(0.070)	(0.088)	(0.470)
N	4,083	4,083	4,083	4,083
R-squared	0.030	0.036	0.033	0.033

Each column is a separate regression for each of the four county-level treatments outlined in Section 4: literacy, urbanicity, average land value, and population. Panel A reports results of the effect of each treatment on total number of children. Panel B reports results of the effect of each treatment on total number of children for the 2nd generation (children of riders). Demographic controls include gender, age, race, and immigrant status. Orphanage-census year fixed effects are included are included in all regressions. Standard errors are clustered at the orphanage-census year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

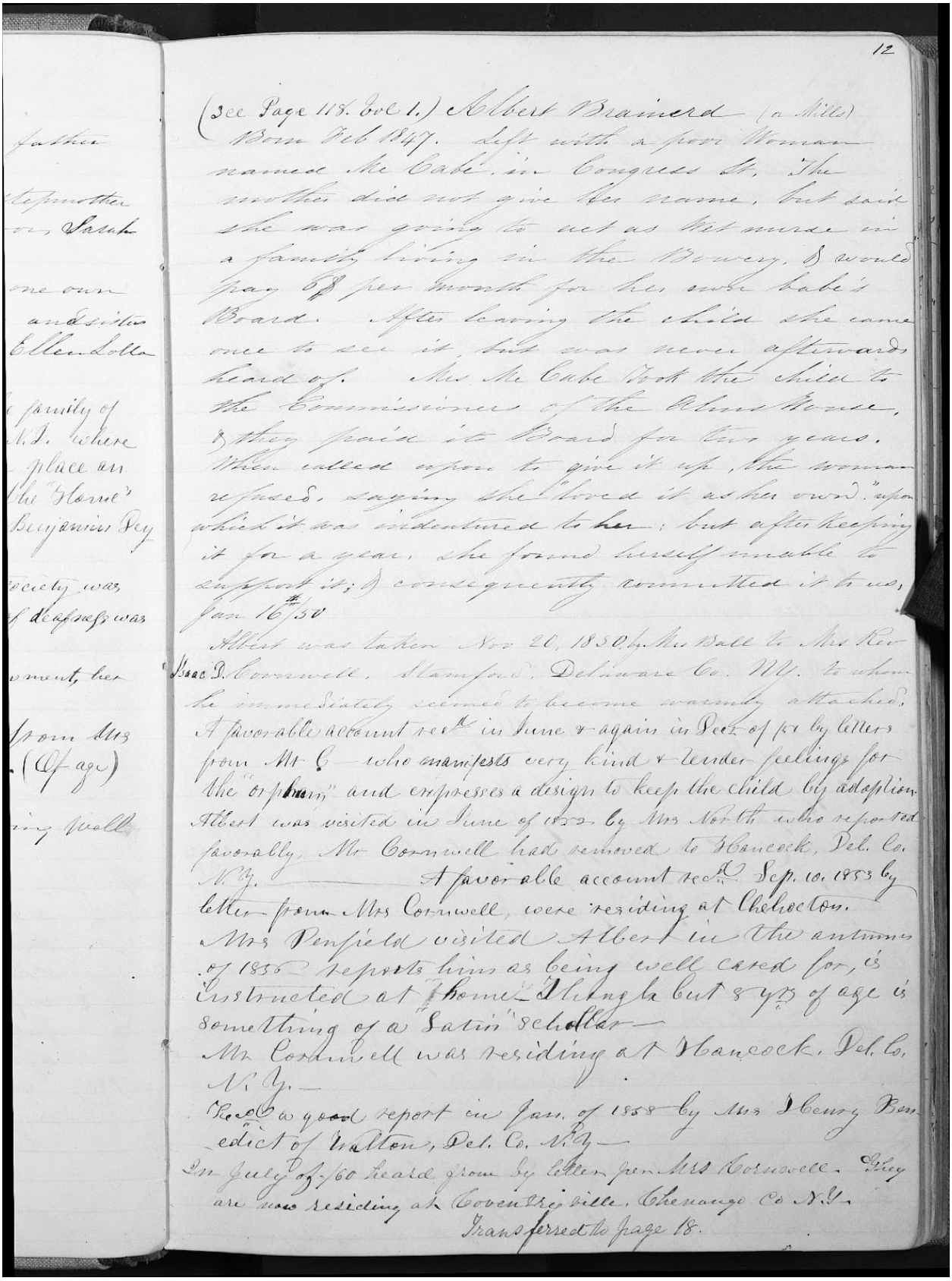
Table 4: Fertility Effects

A Additional Figures and Tables



Source: Making a Difference Project

Figure A.1: Orphan Train Riders Waiting at Train Stop



12

(See Page 118. Vol 1.) Albert Brainerd (a Mulatto)
Born Feb 1847. Left with a poor Woman
named Mc Cabe in Congress St. The
mother did not give her name, but said
she was going to act as Wet nurse in
a family living in the Bowery, & would
pay $3 per month for her own babe's
Board. After leaving the child she came
once to see it, but was never afterwards
heard of. Mrs Mc Cabe took the child to
the Commissioners of the Alms House,
& they paid it Board for two years.
When called upon to give it up, the woman
refused, saying she "loved it as her own", upon
which it was indentured to her; but after keeping
it for a year, she found herself unable to
support it; & consequently committed it to us,
Jan 16th 50

Albert was taken Nov 20, 1850 by Mrs Ball to Mrs Rev
Isaac D. Cornwell, Stamford, Delaware Co. N.Y. to whom
he immediately seemed to become warmly attached.
A favorable account rec'd in June & again in Dec'r of yr by letters
from Mr C — who manifests very kind & tender feelings for
the "orphan," and expresses a design to keep the child by adoption.
Albert was visited in June of 1852 by Mrs North who reported
favorably, Mr Cornwell had removed to Hancock, Del. Co.
N.Y. A favorable account rec'd Sep. 10. 1853 by
letter from Mrs Cornwell, were residing at Chehocton.
Mrs Penfield visited Albert in the autumn
of 1855 reports him as being well cared for, is
instructed at "Home" & being but 8 yrs of age is
something of a "Satin" scholar —
Mr Cornwell was residing at Hancock, Del. Co.
N.Y. —
Rec'd a good report in Jan. of 1858 by Mrs Henry Ben-
edict of Walton, Del. Co. N.Y. —
In July of 1860 heard from by letter from Mrs Cornwell. They
are now residing at Coventryville, Chenango Co N.Y.

Transferred to page 18.

Figure A.2: Example of American Female Guardian Society Ledgers

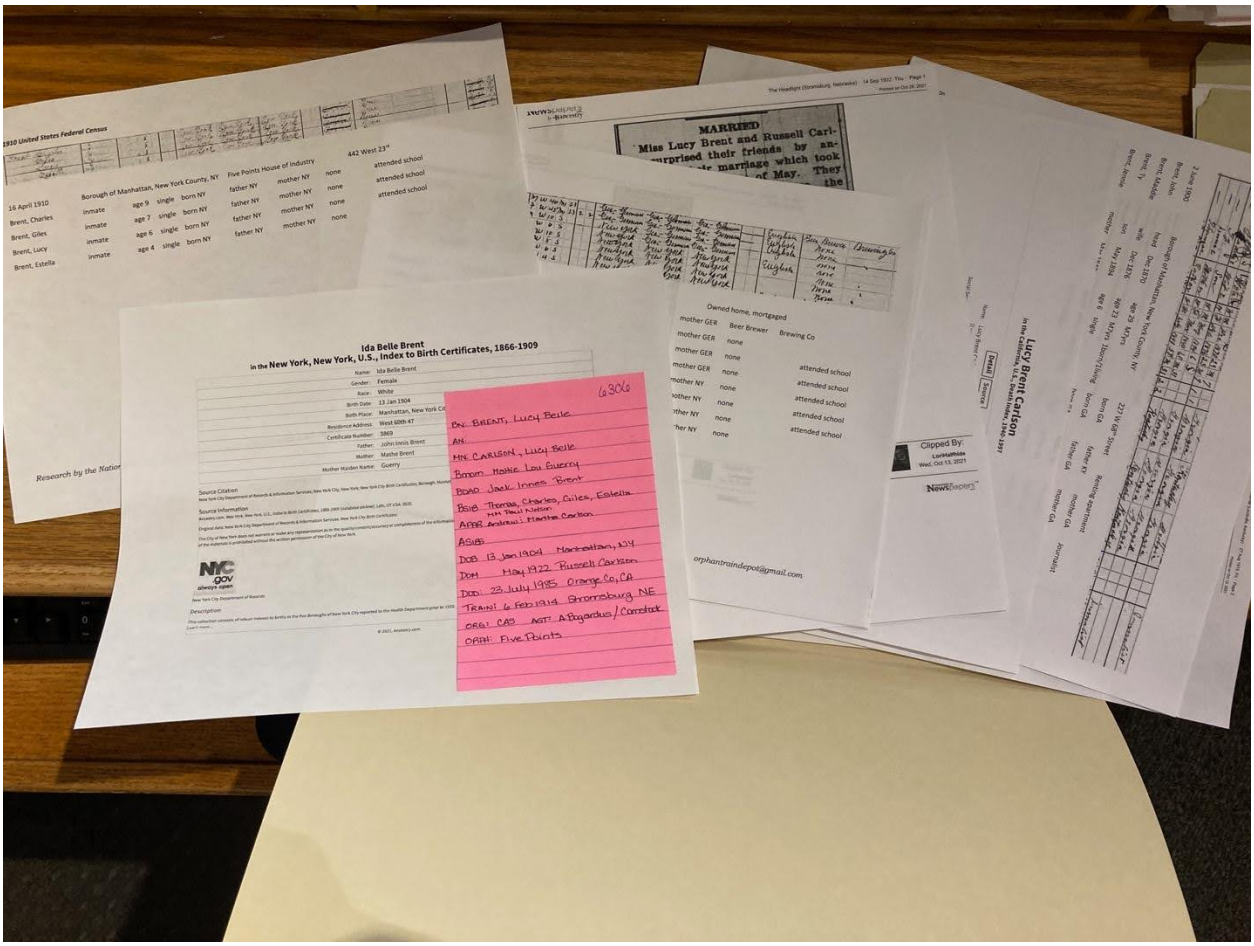


Figure A.3: Example of National Orphan Train Complex Research Document

Last Name	First Name	Age	Last Birthday	Date(s) Placed or Indentured	Name of Foster Parent	Residence of Foster Parent
McLaughlin	Mary Ann	8		September 29, 1854	Ebenezer B. Watson	Waverly, Morgan, Illinois
McLaughlin	Mary	11		September 28, 1854	Ebenezer B. Watson	Waverly, Morgan, Illinois
McQuinn	Thomas	10		September 28, 1854	John L. Gage	Dowagiac, Cass, Michigan
					William M. Heazlit	Dowagiac, Cass, Michigan
Meagher	James	12		April 6, 1854	Abraham Coddington	Yonkers, Westchester, New York
				September 28, 1854	Albert Kencott	La Grange, Cass, Michigan
Morris	William	13		September 28, 1854	Samuel Aaron	La Grange, Cass, Michigan
				November 28, 1854	Isaac Marsh	Cassopolis, Cass, Michigan
Murphy	Edward	14		September 28, 1854	Israel Sable or Salle	Silver Creek, Cass, Michigan
					Mrs. Emmons	Dowagiac, Cass, Michigan
Munger	Isaac E.	14		September 28, 1854	Isaac Bonine	Vandalia, Cass, Michigan
Pointon	George F.	10		September 28, 1854	Mr. [E. P.] Smith of CAS	Michigan (several homes)
Punch	Patrick Phillip	10		September 28, 1854	Samuel B. Poor	Dowagiac, Cass, Michigan
				November 17, 1855	Henry S. Kinnicutt	Keeler, Van Buren, Michigan
Rathbun	William H.	15		September 28, 1854	John H. Callum	Dowagiac, Cass, Michigan
Sneider	John	9		September 28, 1854	Rev. B. B. Nichols	Chicago, Cook, Illinois
Smith	Edward	10		September 28, 1854	Patrick Hamilton	Dowagiac, Cass, Michigan
Smith	James	10		September 28, 1854	Ebenezer M. Bird	Dowagiac, Cass, Michigan

Source: Kidder, Clark (2021) "A History of the New York Juvenile Asylum and Its Orphan Trains: Volume 2" pg. 16

Figure A.4: New York Juvenile Asylum Research Document

	East Midwest	New England	South	West	West Midwest
Female	0.371	0.093	0.191	0.571	0.149
White	0.107	0.254	0.611	0.265	0.002
Placement Age	1.005	0.205	0.12	0.231	0.229
Native	0.245	0.044	0.117	0.353	0.219

This table contains the absolute value of the estimated normalized difference statistics for the covariate in each row and the region in each column. Each column considers the region pair consisting of the Mid-Atlantic Census region (where NYC is located) and the Census region listed in the column. According to Imbens (2017), a normalized difference statistic smaller than 1 in absolute value indicates that the treatment and control groups are comparable. See Imbens (2017) for calculation details.

Table A.1: Imbens Normalized Differences, Pairwise Region Comparisons

Table A.2: Summary statistics, NOTC Data

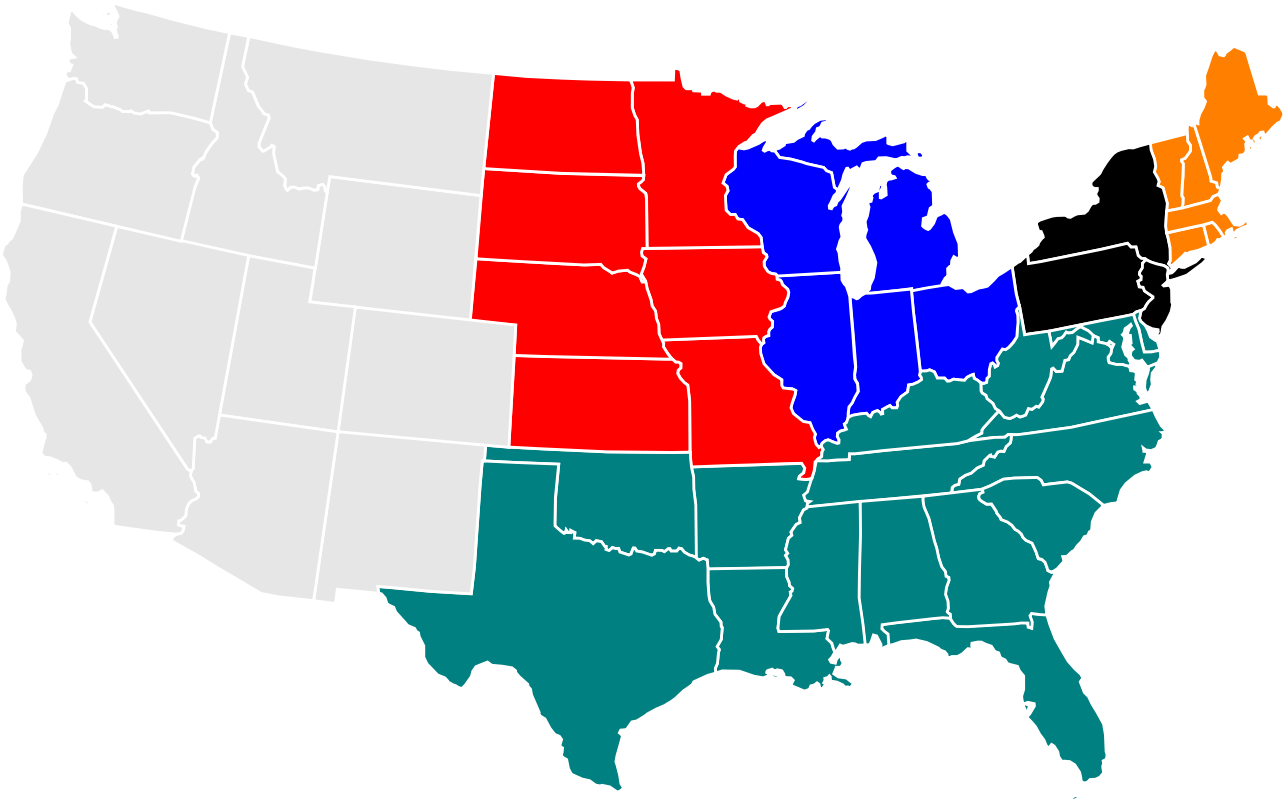
	1850	1860	1870	1880	1900	1910	1920	1930
Age	5.8	6.7	7.8	9.7	6.0	8.2	7.6	11.8
	5.5	5.0	5.3	6.8	5.3	5.0	6.2	5.4
Female	0.5	0.2	0.2	0.3	0.5	0.5	0.6	0.4
	0.5	0.4	0.4	0.5	0.5	0.5	0.5	0.5
White	0.9	0.9	0.9	1.0	1.0	1.0	1.0	1.0
	0.3	0.3	0.3	0.2	0.1	0.2	0.2	0.0
Native	0.8	0.8	0.9	0.9	0.9	1.0	1.0	1.0
	0.4	0.4	0.3	0.3	0.2	0.1	0.0	0.0
Count	13	21	33	261	191	184	94	10

Table A.3: Summary statistics, NYJA Data

	1850	1860	1870	1880	1900	1910	1920	1930
Age	11.2	12.5	12.5	12.9	12.0	-	16.0	-
	2.2	2.7	3.0	4.1	3.9	-	12.7	-
Female	0.2	0.3	0.2	0.3	0.3	-	0.0	-
	0.4	0.5	0.4	0.4	0.4	-	0.0	-
White	1.0	1.0	1.0	1.0	1.0	-	1.0	-
	0.0	0.2	0.1	0.1	0.1	-	0.0	-
Native	0.6	0.7	0.8	0.9	0.9	-	1.0	-
	0.5	0.5	0.4	0.3	0.3	-	0.0	-
Count	20	646	636	1413	620	-	2	-

Table A.4: Summary statistics, AFGS and CAS data

	AFGS		**CAS**	
	1880	1920	1880	1920
Age	10.0	12.4	11.3	10.5
	9.9	4.9	10.1	7.2
Female	0.5	0.3	0.2	0.3
	0.5	0.5	0.4	0.5
White	1.0	1.0	1.0	1.0
	0.1	0.0	0.1	0.2
Native	0.8	1.0	0.9	0.9
	0.4	0.0	0.3	0.2
Count	817	33	748	169



Black = Mid-Atlantic (baseline), Orange = New England, Teal = South, Blue = West Midwest, Red = East Midwest, Grey = West. Classifications made based on U.S. Census categorization.

Figure A.5: Visualization of Regional Treatments