Lifetime and Intergenerational Effects of Place: Evidence from the Orphan Train Movement

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Abstract

Measuring how the geographical location where children grow up affects their long-run outcomes is difficult because families choose where to live based on factors that also influence their children's outcomes. To overcome this, we study the Orphan Train Movement, a large-scale child welfare program from 1853-1929 that relocated orphaned children from northeastern cities to families across the United States. Institutional procedures resulted in quasi-random variation in placement locations based on arrival timing rather than children's characteristics. We digitize archival records and link riders to Census data to measure long-run outcomes across their lifetimes and for their children. We define place using county-level characteristics capturing education, urbanization, wealth, and labor market size. Riders placed in counties with higher education levels, greater urbanization, more wealth, and larger labor markets earn more lifetime income, have fewer children, and are less likely to work in agriculture. These effects persist into the second generation. Examining dimensions separately reveals that urbanization, wealth, and labor market size drive effects. We find important age heterogeneity, where older children show larger marginal gains from better places despite younger children having higher adult baseline earnings. Intergenerational transmission operates through a persistent change to individuals rather than geographic persistence, as effects continue despite high migration from riders' original placement counties. Our findings provide the first causal evidence that place effects transmit across generations.

JEL classifications: N31, N32, I31, J13, J62, R23

Keywords: Place effects, Intergenerational transmission, Migration, Child welfare

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1 Introduction

One of the first questions we ask when introduced to someone new is where they are from. People typically respond to this question by describing the places where they spent their formative years. We ask this question because we believe it reveals something about who the person is today. This common exchange suggests that the place where we grow up may have lasting effects on who we become. This intuition has motivated social scientists to examine how the characteristics of places shape persistent and intergenerational socioeconomic outcomes.

Understanding the effects of place is challenging due to non-random sorting in location selection. The "Moving to Opportunity" (MTO) experiment randomly allocated housing vouchers to low-income families in public housing, allowing them to move from high-poverty to lower-poverty neighborhoods. Early effects showed that features of place significantly shape adult mental and physical health related outcomes, but found no effects on employment or earnings (Katz, Kling, & Liebman, 2001; Ludwig et al., 2013). However, the long-run impact of neighborhoods is especially salient for children. Children who grow up in lower-poverty neighborhoods are more likely to have higher earnings and educational attainment moving into adulthood (Chetty, Hendren, & Katz, 2016). Studies on forced displacements of families from public housing demolitions similarly find positive neighborhood effects (Chyn, 2018). These positive effects are amplified for younger children who experience longer exposure to better neighborhoods (Chetty & Hendren, 2018a) demonstrating that childhood environment causally shapes long-term well-being.

Despite these findings, key gaps remain in the current literature. First, defining place based solely on poverty measures may mischaracterize the important channels of "opportunity" relating to location. MTO examined moves from high-poverty to lower-poverty urban neighborhoods, but places differ along many dimensions such as education levels, labor market size, population density, and wealth, which may independently affect outcomes. Alternative features of place, which may not vary between these localities, may have additional consequences on shaping individual outcomes. Second, MTO involved short-distance moves within metropolitan areas, limiting our understanding of how children are impacted by place across diverse geographic settings, including rural areas. Third, while longer run outcomes have revealed age heterogeneity in treatment effects, we still lack evidence on full life-cycle and intergenerational impacts. Do the benefits of place for one generation persist to the next? Finally, the treatment of place for the child is combined with the movement of the household in MTO, making it difficult to disentangle individual-level place effects from household level mechanisms.

This paper fills these gaps using novel evidence from a historical child welfare program in the United States. We identify the causal effects of place by examining 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 relocated hundreds-of-thousands of displaced and orphaned children from New York City and other northeastern cities to families throughout the United States, representing one of the largest and longest child welfare programs in American history. We focus on children from three major New York City Protestant orphanages whose placement procedures generate variation that we leverage for causal identification of place. Our identification strategy exploits institutional constraints that created quasi-random variation in placement locations. We digitize a novel set of historical records to reveal children were sent out based on arrival, prioritizing those who were at the orphanage the longest (Kidder, 2003). Conditional on children possessing characteristics that made them eligible for the Orphan Train, institutional capacity constraints resulted in children being placed in locations based on their time of arrival at the orphanage rather than their individual characteristics. This resulted in quasi-random assignment to destination counties among those that the orphanages canvassed. We verify our identification assumption by showing that observable child characteristics at admission do not systematically predict destination county characteristics. We also demonstrate our results are robust across several specifications.

We define place at the county level using four characteristics measured at the time of placement: literacy rates, urbanicity/residential development, land value, and population. These dimensions capture aspects of local opportunity (education, urbanization, wealth, and labor market size) that contemporary theory suggests shape economic outcomes (Chetty & Hendren, 2018a; Glaeser & Maré, 2001; Moretti & Yi, 2024). Our approach aims to construct a historical measure comparable to the poverty-based neighborhood indices that are used in modern studies (Chetty & Hendren, 2018a; Chyn, 2018), by using variables that proxy for the underlying conditions. By examining each dimension separately, we identify which specific features of place independently and in aggregate drive long-run effects. We classify counties as high versus low-opportunity based on whether they rank above or below the median for each characteristic and construct an opportunity index aggregating across all four dimensions.

We digitize and combine archival data from historical documents maintained by organizations involved in the Orphan Train Movement with a longitudinally linked panel of Census data from the Census Tree project, allowing us to track long-run outcomes for both the riders themselves and their descendants. Using the opportunity index that aggregates across all four county characteristics, we find that riders placed in high-opportunity counties earn 1.15 percentile points more in occupational income scores, have 0.09 fewer children, and are 4.4 percentage points less likely to work in agriculture compared to riders placed in low-opportunity counties. These effects persist and amplify in the second generation with income gains of 1.24 percentile points, fertility reductions of 0.13 children, and farming reductions of 4.3 percentage points. Effects are largest at the very highest levels of opportunity, with riders earning 5.70 percentile points more in average occupational income than the lowest opportunity riders.

Examining each dimension of place separately reveals which features of opportunity drive these results. Urbanicity generates the largest gains in income (2.42 percentile points for the first generation and 2.92 for the second generation) and reduces farming propensity by approximately 10-11 percentage points across both generations. Land value increases income by 1.71 and 3.83 percentile points for first and second generations respectively, while population size increases income by 2.24 and 2.43 percentile points for each respective generation. Notably, we observe no effects of literacy on occupational income scores for either generation. Urbanization, wealth, and labor market size matter for long-run changes in lifetime earnings. Fertility effects are mostly driven by urbanicity and population (0.16 and 0.24 fewer children in the first generation), with second generation effects either persisting or growing in size (0.30 and 0.22 fewer children respectively). The consistent pattern of effects persisting or amplifying from first to second generation demonstrates that place-based advantages compound beyond the initially treated group. We explore heterogeneity in these treatment effects by age at placement. Consistent with prior evidence on exposure effects, younger children (placed before age 13) placed in high-opportunity counties achieve higher baseline earnings (1.91 percentile points) than older children. However, older children show larger marginal income gains (7.29 percentile points) from high-opportunity placements, suggesting diminishing returns when baseline human capital is relatively higher through earlier placements.

Our findings make several important contributions to understanding how place shapes long-term economic outcomes. First, we provide causal evidence on which dimensions of place drive long-run economic outcomes. While existing studies primarily examine how neighborhood poverty rates affect children (Chetty & Hendren, 2018a; Chyn, 2018), we separately identify the effects of education levels, urbanization/residential development, wealth, and labor market size demonstrating that residential development, wealth and labor market size matter substantially while local literacy rate has no effect. Second, we extend place effects research beyond typical urban settings by studying placements across diverse geographic contexts, providing evidence that place effects operate across a wider range of environments than previously explored. Third, we provide the first causal evidence of intergenerational transmission of place effects, showing that the benefits of individuals growing up in high-opportunity counties extend to their children, with effects that either persist or amplify in magnitude across generations. Finally, we document important heterogeneity in place effects by age at placement: younger children have higher baseline earnings from placement itself, older children show larger marginal gains from high-opportunity counties, suggesting that baseline human capital shapes the returns from environmental improvements in ways that complement existing evidence on exposure effects.

Beyond identifying place effects, we shed some light on the mechanisms through which neighborhoods shape outcomes and transmit across generations. We show that household characteristics matter substantially. The households in which riders are placed generate effects approximately five times larger than place effects for income, yet place effects persist even after controlling for household composition. This results provides nuanced insight into the effects of place. At the most micro-level, households, as a feature of place, matter the most in shaping individual outcomes, whereas macro-level environments matter but to a lesser degree. This addresses a key challenge in the place effects literature where families move together, making it difficult to separate neighborhood influences from endogenous household-level factors (Oreopoulos, 2003). Additionally, we demonstrate that intergenerational transmission operates through shaping individuals rather than geographic persistence. Children of orphan train riders, on average, do not remain in their parents' placement counties, yet second generation effects persist and grow. This suggests that place durably shapes human capital or capabilities in ways that parents transmit to their children independent of location, providing novel evidence on how neighborhood effects become embedded across generations, with important implications for evaluating the full social returns to place-based investments.

The remainder of the paper is structured as follows: Section 2 provides the historical background of the Orphan Train Movement; Section 3 describes our data collection, digitization, and linkage procedure; Section 4 presents the empirical strategy for measuring place effects; Section 5 reports the main results for first and second generation outcomes and explores heterogeneity across age, gender, time period, and geography; Section 6 investigates potential mechanisms for place effects; Section 7 discusses the implications of the findings; and Section 8 concludes.

2 Background

2.1 Understanding the Effect of Place

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 are likely have intergenerational impacts, as children are very likely to live close to 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 public housing demolitions, finding positive adult labor market effects that cannot be explained by parental effects or changes in adolescent criminal behavior. Furthermore, Chetty and Hendren (2018a) emphasize that the effects of childhood exposure to higher-opportunity neighborhoods increase with the duration of exposure. Together, these findings show that differences in outcomes across places are driven by the opportunities found in those places.

Another strand of literature focuses on how parental experiences can affect child outcomes. Buckles, Price, Ward, and Wilbert (2023) argue that assortative matching, where individuals tend to marry within similar economic strata, limits intergenerational mobility. Barr and Gibbs (2022) find that exposure to the Head Start program improved educational attainment and reduced teen pregnancy and crime among children whose mothers likely attended a Head Start program. Finally, Chetty, Hendren, Kline, and Saez (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.

We acknowledge a parallel project by Abrahams and Keniston (2025) who examine the effects of adoption and place using the Orphan Train Movement.[1] We provide several important distinctions. We examine effects over the life course and extend the analysis to intergenerational effects of place. Our empirical approach utilizes a variety of analyses examining the relative effects of place, in order to make causal comparisons among orphan train riders. We examine potential mechanisms utilizing theoretical predictions directly from the modern place literature (Chetty & Hendren, 2018a; Chetty et al., 2014; Chyn & Katz, 2021). Our sample includes individuals from a larger subset of orphanages and extends through the later half of the program.

Due to data limitations, previous work has not been able to identify the long-lasting and intergenerational effects of place. We identify these impacts of place by combining archival records from orphanages on Orphan Train riders with a longitudinally linked panel of full-count U.S. Censuses provided by the Census Tree Project (Price, Buckles, Van Leeuwen, & Riley, 2021).

We define place using four county-level characteristics measured at the time of placement: literacy rates (percent of population identifying as literate), urbanicity (the fraction of individuals living in Census-designated places with population of at least 2,500), land value (average value of property), and population. These dimensions capture theoretically distinct channels through which place affects economic opportunity. Literacy rates proxy

[1]The first version of our manuscript was posted on SSRN on May 1, 2025, their version was posted on NBER in September 2025.

for education access. Urbanization reflects urban agglomeration of industries, wage growth opportunities, and exposure to non-agricultural opportunities (Glaeser & Maré, 2001). Land values proxy for average local wealth as a comparison to poverty rates. Population captures labor market size, employment diversity, and matching opportunities (Moretti & Yi, 2024).

Our approach builds on contemporary studies that measure neighborhood quality primarily through poverty rates (Chetty et al., 2014; Chyn, 2018). Chetty and Hendren (2018b) find that areas with better schools, lower crime, and stronger family structures produce better mobility outcomes. By separately examining distinct dimensions of opportunity, we identify which specific features independently and in aggregate drive long-run effects. This decomposition is particularly valuable in our setting because Orphan Train riders were placed across a large spectrum of American communities, from dense urban centers to remote agricultural areas, creating substantial variation along each dimension.

Our variable selection balances theoretical motivation with historical data constraints. These four characteristics represent the most reliable county-level measures available consistently throughout the Orphan Train Movement (1853-1929). Early censuses, particularly from 1850-1870 when many placements occurred, provide limited county-level data. While we would ideally include additional dimensions such as a direct poverty rate consistent measurement of these factors is not feasible across our full sample period.

We classify counties as "high-opportunity" or "low-opportunity" if they rank above or below the median threshold for each treatment dimension. A county's designation as high-opportunity is specific to each dimension we examine. For example, a county may be high-opportunity in terms of literacy rates while simultaneously being low-opportunity in terms of land values. We estimate effects using two approaches: first, we construct an opportunity index aggregating across all four dimensions; second, we examine each dimension independently. This dual approach allows us to assess both the aggregate effects of opportunity and isolate which specific dimensions drive long-run effects.

Based on previous findings, we expect Orphan Train riders placed in counties with more economic opportunity to see improved labor market outcomes on average. Due to 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 (D. A. Black, Kolesnikova, Sanders, & Taylor, 2013; Dribe, Oris, & Pozzi, 2014; Jones & Tertilt, 2008; Lindo, 2010).

2.2 What was the Orphan Train Movement?

In the mid-19th century, an increase of immigration and migration to urban centers rapidly increased population, particularly in New York City, the largest city in the United States. These demographic changes resulted in limited local economic opportunities, low wages, and high health hazards, particularly among working class and immigrant workers (O'Connor, 2004). One severe consequence of this rapid influx was an increase in the number of vagrant children, many of whom did not have additional family or resources in the local community. In the 1850s, estimates of the size of this population in New York City ranged conservatively from 3,000 among police reports to 40,000 (O'Connor, 2004).

Public child welfare institutions were underdeveloped during this period, with little regulation or government involvement. The care of displaced children belonged to religious or civic institutions with inadequate resources, leading to an influx of children in orphanages in the city. At the same time, families in communities throughout the United States needed children to assist with agricultural labor and other economic activities on the expanding western frontier. To help solve these problems, orphanages began the Orphan Train Movement, which relocated orphans from primarily New York City to families throughout the United States. The purpose of the program was to place orphaned, surrendered, and displaced children, defined as "riders", in an environment that could serve their needs (Kidder, 2003).

The situation is summarized in the early reports from participating organizations, "The extent of our accommodations forbade their increase" [...] "calls [from Western states] were now made upon us for children, and very soon our anxieties were not to find homes for the children, but children for the homes" (New York Juvenile Asylum, 1856, p. 21). These institutional constraints created conditions where the relative timing of a child's arrival to an orphanage, not their characteristics, completely determined their destination. This feature provides a quasi-experimental setting for our study to understand the effects of place.

2.3 Orphan Train Placement Process

> *"We formed little companies of emigrants, and, after thoroughly cleaning and clothing them, and, first selecting a village where there was a call or opening for such a party, we dispatched them to the place."* *-Charles Loring Brace, 1880*

A significant portion of Orphan Train riders were placed by orphanages affiliated with Protestant churches, which quasi-randomly placed children in locations across the United States.[2] Using a representative town (Town A) and orphanage (New York Juvenile Asylum (NYJA)), the relocation process followed 5 steps:

1. **Social workers establish placement interest in Town A:** Full-time NYJA employees living outside New York City work with local civic and religious leaders to establish interest among families in Town A. These social workers determined the number of riders that town A was willing to accept.

2. **Social workers send interest estimates back to NYC:** Once interest is established, social workers transmit the number of riders Town A would accept to NYJA headquarters in New York City. These estimates were transmitted by both mail and telegraph.

[2]Other organizations, such as the New York Foundling Hospital affiliated with the Catholic Church, varied in their placement procedure. Families in towns that were being canvassed could request a the child being sent to posses certain set of characteristics. This resulted in the match between the family and child essentially occurring prior to the child being sent to the location. This placement process may result in non-random variation in location. To avoid this potential bias, we exclude these riders from our sample.

3. **Orphanage purchases passes on next train going to Town A:** Once NYJA headquarters receives the number of children Town A is willing to accept, they purchase the necessary number of passenger tickets to send children to Town A.

4. **Eligible children were placed on the next train to Town A:** Conditional on meeting minimum eligibility requirements[3], children are selected to board the next train to Town A using a "first in, first out mechanism"[4], where eligible children who have been in the orphanage longer have priority over newer arrivals to the orphanage. While orphanages in New York City were severely capacity constrained at the start of the Orphan Train Movement in 1853, by 1859 it had become necessary to "dispatch a company [of children] West every 6 if not every 4 weeks" to meet demand for Orphan Train riders outside New York City (Kidder, 2003). Importantly, the implication of this procedure imply that the exact county chosen for a child is orthogonal to latent child characteristics, and is therefore plausibly exogenous. We exploit this source of plausibly exogenous variation to determine the persistent effects of place.

5. **After arrival in Town A, families select children:** Once children arrived in Town A, a town meeting was called where local religious and civic leaders assist social workers in placing riders with families (Brace, 1880)[5] Although there is potential for endogenous selection at this stage, we utilize the plausibly exogenous variation in Step 4 to determine the causal effect of place.

We make an important distinction between Orphan Train "riders" and "non-riders" as comparisons between these two groups can lead to biased estimates. Specifically, ineligible children are always non-riders and may possess latent characteristics that could influence the outcomes we measure. The specific procedure we use in identifying an orphaned child

[3] A child was considered eligible if they had no physical or mental disabilities, were not serving punishment for a crime, and were toilet-trained (see Kidder (2003) for more details).

[4] See Kidder (2003) for discussion on how this was implemented for NYJA, whose placement process was similar to other NYC orphanages.

[5] See Figure A.1 of a visualization of the endogenous selection process.

as a rider is described in section 3.3, and we identify and drop non-riders from our sample. Non-riders are, therefore, not in the analysis. It should be noted that the participating orphanages did not formally identify children belonging to either group. Often these children were retrospectively mentioned as being "placed-out" or "emigrated" in annual reports or ledgers (O'Connor, 2004). We use this information to help construct the rider variable. This classification requires detailed institutional records, which we describe in the following section.

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, linking 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.[6] 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

[6]The Orphan Train Movement operated through 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 organizations 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.

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.[7]

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.2, A.3, and A.4 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, gender, and age. From the ledgers and research documents, we find placement date, placement location, placing organization, and their surname.

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 for which we have other primary documentation.[8] These research documents are extremely valuable as they help fill in the sample with riders who were placed out by other Protestant orphanages for which we do not have primary source data.

3.2 Linking to Census Data

To link orphan records with the U.S. Census, we use a probabilistic matching model that uses first and last name, year of birth, and state of residence.[9] Results are shown in Table 1.

[7]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.

[8]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

[9]The specific Stata command used is reclink.

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.[10] This matching process results in about 60% of the orphans in our data being linked to the U.S. Census.[11] Of the 18,288 orphans for whom we have data, we successfully linked 11,052 to at least one historical census.

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.[12] This data allows us to follow individuals for up to 90 years and enables us to examine labor market outcomes and fertility.

A useful feature of these data is that they follow both individuals and households over time. We use this feature to create an intergenerational sample of the children of the Orphan Train riders by linking parents to children. To do this, we locate the households in the Census where riders were the 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 children of riders through adulthood and estimate intergenerational effects.

3.3 Defining Orphan Train Riders

Since these data contain both riders and non-riders, it is necessary to distinguish them to examine the effect of place[13] as we compare outcomes across riders. 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, emigrated, or placed-out as indicated by historical ledgers

[10]This matching method is closest to the process used in Abramitzky, Boustan, and Eriksson (2014).
[11]See Price et al. (2021) for a discussion of linkage rates.
[12]See the Census Tree Project website for more information.
[13]In our analysis, we drop individuals who are orphans but are determined to be non-riders

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 subsequent 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).[14] Our final identification of riders is consistent with the estimated distribution of riders from the Children's Aid Society in Figure A.5, which shows that many riders were placed in New York and Illinois.

Table 2 summarizes the key steps in the data linkage and cleaning process and reports how the process affects our sample size for the first generation. The two steps of the data cleaning process that result in substantial data loss are linking to U.S. Census records (60% of all individuals in our digitized data link to at least one census record) and verifying riders, which eliminates nearly half of the remaining sample. This raises the concern that our sample may not be representative of all Orphan Train riders. To address this concern, we examine how demographic characteristics vary between each step in the data cleaning process.[15] We find that the subset of individuals who are verified riders have demographics similar to the set of individuals who are linked to at least one full-count census record. Specifically, the set of all Census-linked individuals and the subset of verified riders are 26% and 25% female, 98% and 99% white, are 82% and 85% native-born, and have average placement ages of 12.8 and 13.1, respectively. As we have no baseline value for the true number of Orphan Train riders we rely on the estimated total of riders sent by the Children' Aid Society. Our best estimation of the true number of Orphan Train riders among Protestant organizations among our sample organizations is approximately 100,000. We conservatively estimate initially identifying 18% of the potential sample and after strict restrictions reduce the sample to 20% of the original

[14]This approach naturally underestimates the true number of riders in our sample. However, it is impossible to distinguish between eligible riders and ineligible non-riders for children in New York County. Conservatively, we also remove any physically surrounding county. This approach removes the potential for biased comparisons among eligible and ineligible children.

[15]We start with the sample of orphan riders linked to at least 1 full-count census record, since our demographic information relies on full-count census records.

identification, or 3.5% of total riders[16].

4 Estimation Strategy

To estimate the local average treatment effect (LATE) of place on socioeconomic outcomes, unobserved rider characteristics that affect occupational income score, fertility, and farming must be uncorrelated with treatment assignment, which we define as being placed in a high-opportunity area on one of several dimensions: literacy, urbanicity/residential development, wealth, and population.

4.1 Defining and Analyzing Place

To estimate the county-level effects of the Orphan Train Movement on long-run outcomes, we first identify whether the county to which each rider was sent was above or below the median of several county characteristics: literacy, urbanicity/residential development, land values, and population. These characteristics are indicative of higher access to education, higher density, more wealth, and larger labor markets,[17] all factors that are correlated with greater economic opportunity (Chetty et al., 2016). These place-based institutional factors are measured in each county are estimated in each county where an orphan was placed using the census year nearest to when a child was sent to a given county.

We define treatment in our context as an indicator for being placed in a county that is above-median on each of these.[18]

[16] Summary statistics are shown by orphanage-census year in Tables A.1, A.2, A.3

[17] Since we are estimating over a large time period with multiple recessions and a changing economic landscape, we use population as an acyclic measure of labor market size, which is related to labor market diversity, employment, and earnings (Glaeser & Maré, 2001; Moretti & Yi, 2024).

[18] We pool treatment definitions across census years in our main specification. This approach ensures consistent treatment thresholds across cohorts and avoids mechanical endogeneity that would arise from defining treatment based on census-specific medians, which reflect the endogenous composition of orphanage placement cohorts. Our placement year by orphanage fixed effects control for systematic trends in destination characteristics within orphanages over time. This approach maximizes statistical power while providing a clear interpretation: we estimate the average effect of placement in high-opportunity counties as defined by the full distribution of Orphan Train destinations.

Each county-census year combination that had a rider placed within a 5-year window to that census year will be assigned an above or below median indicator for each treatment type. This approach results in 119 unique placement counties. We then first estimate the following equations:

$$Y_{ico} = \alpha + \tau Count_{ic} + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{1}$$

where $Count_{ic} = \sum_{k=1}^{4} D_{k,ic} \in \{0, 1, 2, 3, 4\}$ and,

$$Y_{ico} = \alpha + \sum_{j=1}^{4} \delta_j \cdot \mathbf{1}\{Count_{ic} = j\} + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{2}$$

to generate a "opportunity index" for measuring the effects of place on outcomes. Equation 1 has $Count_{ic}$ for individual i in county c measure the relative intensity of opportunity a county has indexed between 0 and 4 by the number of above-median county characteristic k, X_i' are time-invariant demographic controls and γ_{po} represents placement year p by orphanage o fixed-effects. Equation 2 estimates non-linear effects by including separate indicators for each opportunity level, allowing us to test whether returns to opportunity are constant or increasing. $\mathbf{1}\{Count_{ic} = j\}$ indicate the number of above-median treatments that a county c possesses.

These estimations give us the the intensity of opportunity effect with our parameters of interest being τ and δ_j respectively denoting the effect of being in higher intensity opportunity places. One limitation with this approach is that we can not distinguish the type of treatment that is driving these effects. We explore this limitation be estimating the following regressions:

$$Y_i = \alpha + \tau T_{ic} + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{3}$$

and,

$$Y_{ico} = \alpha + \tau_1 T_{ic}^L + \tau_2 T_{ic}^R + \tau_3 T_{ic}^V + \tau_4 T_{ic}^P + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{4}$$

where equation 3 has T_i is a county characteristic treatment variable. $T_i = 1$ if rider i was placed in a county with above-median treatment value, 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_{po} represents placement year by orphanage fixed-effects. The coefficient on treatment, τ, measures the effect of being placed in an above-median county, and ϵ_{ito} is the error term.

A potential concern is that the four treatment definitions are correlated, which could lead us to misattribute effects when estimating them separately. To address if a particular treatment is driving the results, we estimate 4 which includes all four treatments simultaneously, allowing us to assess whether particular dimensions dominate.[19] T_{ic}^L is an indicator for being in an above or below median opportunity county with respect to literacy, T_{ic}^R is an indicator for being in an above or below median opportunity county with respect to residential development, T_{ic}^V is an indicator for being in an above or below median opportunity county with respect to land value, and T_{ic}^P is an indicator for being in an above or below median opportunity county with respect to population. τ_1 - τ_4 are the coefficients of interest measuring the effect of each treatment on our outcomes.

Our primary outcome variables Y_i for regressions 1 - 4 are a measure of income, a measure of fertility, and the likelihood of farming in adulthood. To measure the effect of place on labor market outcomes, we use the occupational income score, which reports the median total income (in 1950 dollars) of individuals observed in that occupation in 1950. Then we calculate the individual-level average across census years where an individual is 25-54

[19] Recent work by Goldsmith-Pinkham, Hull, and Kolesár (2024) has shown that including multiple treatment definitions in a linear regression may fail to account for convex averages of heterogeneous treatment effects. Appendix B explores specifications with all interactions. We interpret equation 3 as our primary estimates and use equation 4 as suggestive evidence for which of our dimensions matter the most.

years old.[20;21] Our fertility measure is the maximum number of own children observed across all census years where an individual reports having children. Our farming measure is a binary indicator that measures whether an individual is ever recorded as living on a farm in adulthood.

4.2 Randomness in Rider Placement Location

> *"The decision about where to place a child was made up almost entirely on the basis of which alternative was most readily available at the moment the child needed help" - Stephen O'Connor, 2004*

Our identification strategy relies on quasi-random assignment of riders to placement counties. We find descriptive evidence of this randomness 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."[22] An 1859 report of the New York Juvenile Asylum describes the mechanism used to select children to be Orphan Train riders: "[The Superintendent] of the Asylum [is] to select 50 children to be sent west... and to keep this class permanently organized, filling vacancies as children are withdrawn from it."[23]

This evidence suggests a"first-in-first-out" mechanism was used to determine which children were sent on Orphan Trains, with placement locations depending on when an eligible child arrived at the orphanage rather than on child characteristics. Unfortunately, due to limited data, we cannot determine exactly when riders arrived at the orphanage. However, because of the rate at which the children were placed out, we can confidently assume that whether a rider was placed in one county versus another was orthogonal to any unobservable

[20]This age range is the Bureau of Labor Statistics definition for "prime-age".

[21]If an individual changes occupation across census years, we observe that change and the average occupational income score would reflect that new income.

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

[23]From the March 31, 1859 NYJA board meeting, see Kidder (2003)

characteristics of the rider that could influence long-run outcomes.

We test this assumption quantitatively by examining whether baseline rider characteristics predict treatment assignment. Table 3 compares mean characteristics of riders placed in low-opportunity (0-1 above-median treatments) versus high-opportunity (3-4 above-median treatments) counties. We find no statistically significant differences in gender, race, or placement age between these groups. Native riders are 3.5 percentage points more likely to end up in a low-opportunity county which, although significant, is economically small.

Table 4 presents regression-based balance tests, by regressing the opportunity index (treatment) on rider characteristics (covariates) and orphanage-by-placement-year fixed effects. In column 1, we find no individually statistically significant relationship between rider characteristics and opportunity level with the exception of native status. We observe a marginally jointly significant (F-statistic = 2.41) relationship in the full-sample. Column 2 restricts the sample to native-born riders only and shows no individually or jointly significant (F-statistic = 2.13) relationships between rider covariates and placement county opportunity levels, failing to reject balance across treatment. We elect to keep our primary specification with non-native riders as the differences are economically small and only marginally significant. Appendix C shows our results are robust to this restriction.

Appendix Table A.4 examines balance for individual treatment dimensions separately. Panel A compares riders placed in counties with greater residential development and finds no statistically or economically significant differences. Panel B compares riders placed in wealthier versus poorer counties and finds no significant differences by gender, small differences in race (0.008) and placement age (-0.363), and a difference in native-born status (0.05) significant at the 1% level. Panel C compares riders placed in more versus less populated counties and finds no statistically or economically significant differences. Panel D compares riders placed in counties with literacy rates above versus below the national median, finding no significant differences except for a 0.5 year difference in placement age and a 0.02 percentage point difference in rider literacy both of which are statistically significant but economically small. While some individual treatment dimensions show small imbalances, these differences are economically insignificant and we control for all baseline characteristics in our regressions.[24] The overall balance results support quasi-random assignment to placement counties.

5 Results

To measure the effect of place we examine the differences between riders who went to high-opportunity versus low-opportunity counties. Each outcome is examined first for riders (First Generation) and then for their children (Second Generation) in the following sections.

5.1 Combined Effects of Place

We begin by examining the combined effects of place using our opportunity index approach. Table 5 presents results from estimating equations 1 (columns 1, 3, and 5) and 2 (columns 2, 4, and 6) where treatment is defined by the number of above-median county characteristics a placement location possesses. The table displays results across three outcomes: occupational income score (columns 1-2), fertility (columns 3-4), and farming propensity (columns 5-6). Panel A reports results for first-generation riders, and Panel B for second-generation riders.

Beginning by examining effects of place on lifetime earnings potential. While occupational income scores are derived from income, the measure was originally conceived as "a method of scaling occupations - essentially a way of turning occupation into a continuous measure" of occupational quality (Sobek, 1995). Because of this, we standardize our occupational income scores into percentiles, so our coefficients of interest are best understood as percentile changes

[24] Appendix Tables A.5 and A.6 present regression-based balance tests and normalized differences for individual treatment definitions. While some statistically significant coefficients appear, normalized differences remain below 0.5 for nearly all comparisons, suggesting treatment and control groups are comparable (Imbens & Rubin, 2015). Imbalances do not appear systematically across treatment dimensions, and we control for all baseline characteristics in our specifications.

in the occupational quality distribution.

Panel A column 1 indicates that each additional opportunity dimension gained increases lifetime average occupation income score (1.14 percentile points). This increases correspond to roughly a 3% increase in average earnings potential for every opportunity index increase for the first generation. Column 2 reveals that these results are unable to detect a significant effect indicative of a linear increase, rather the increases in occupational income scores are mostly driven by being placed in very high opportunity counties (5.70 percentile points). This increases correspond to roughly a 14% increase in average earnings potential for the first generation. For fertility in columns 3 and 4, we find that riders in high-opportunity counties have less children (0.08 fewer children), with those in the high opportunity (treatment=3) counties driving the opportunity index result (0.27 fewer children). For farming in columns 5 and 6, we find that riders in higher opportunity counties are less likely to farm in adulthood (4.4 percentage points), with those in the high (treatment=3) and very high opportunity (treatment=4) counties driving the opportunity index result (11.0 and 16.7 percentage points).

Panel B column 1 indicates that each additional opportunity dimension increases lifetime average occupational income score for second generation individuals (1.24 percentile points). Again, this increases correspond to roughly a 3% increase in average earnings potential for every opportunity index increase for the second generation. Column 2 reveals that these results are unable to detect significant effects for low or medium or very high opportunity counties, with increases driven by high opportunity (treatment=3) counties (4.67 percentile points).This increases correspond to roughly a 11% increase in average earnings potential for the first generation. For fertility in columns 3 and 4, we find that second generation individuals in higher opportunity counties have fewer children (0.13 fewer children), with those in the high opportunity (treatment=3) very high opportunity (treatment=4) counties driving the opportunity index result (0.46 and 0.49 fewer children). For farming in columns 5 and 6, we find that second generation individuals in higher opportunity counties are less likely to farm in adulthood (4.3 percentage points), with those in high (treatment=3) and very high opportunity (treatment=4) counties driving the opportunity index result (15.9 and 10.8 percentage points).

5.2 Individual Effects of Place

Table 6 displays the results from equation 3 (columns 1-4) and equation 4 (column 5) with occupational income score as the outcome across our four county-level treatment definitions: literacy (column 1), urbanicity/residential development (column 2), land value (column 3), and population (column 4). Column 5 includes all four treatments simultaneously. Panel A displays results for first generation riders, and Panel B displays results for second generation riders.

The estimates in Panel A indicate that when comparing riders in high and low-opportunity counties, we see no significant effects on average occupational income score using literacy treatment definition, but significant positive effects for the other three treatment definitions: urbanicity (2.42 percentile points), land value at the 10% level (1.71 percentile points), and population (2.24 percentile points). These increases correspond to roughly a 6%, 4%, and 5% increase in average earnings potential for the first generation, respectively. Column 5 shows that when including all treatments simultaneously, urbanicity remains significant (1.78 percentile points), while the other coefficients lose statistical significance. The estimates in Panel B indicate that, as with the first generation, we find no significant effect using our literacy treatment definition for the second generation. We find significant positive effects for the other three treatment definitions: urbanicity (2.92 percentile points), land value (3.83 percentile points), and population (2.43 percentile points). These increases correspond to roughly a 7%, 9%, and 6% increase in average earnings potential for the second generation, respectively. Column 5 shows that when including all treatments simultaneously all coefficients lose statistical significance at the 1% and 5% level with land value (2.84 percentile points) significant at the 10% level.

Table 7 presents the effects of placement in high-opportunity versus low-opportunity counties on fertility. The table displays results from equation 3 (columns 1-4) and equation 4 (column 5) with the total number of children observed in adulthood as the outcome variable across our four county-level treatment definitions. The table structure remains the same as Table 6. Panel A displays results for the first generation and Panel B for the second generation.

The estimates in Panel A indicate no statistically significant effect of placement for our literacy and land value treatment definitions for first-generation riders. However, columns 2 and 4 show that riders placed in a high-opportunity county have fewer children when considering our other treatment definitions: urbanicity at the 10% level (0.16 fewer children) and population (0.24 fewer children). Column 5 shows that when including all treatments simultaneously, population remains significant (0.22 fewer children). The estimates in Panel B show no significant treatment effects for literacy for second-generation riders. Columns 2 through 4 show significant effects for urbanicity (0.30 fewer children), land value (0.32 fewer children), and population (0.22 fewer children) among second-generation riders in high-opportunity counties compared to those in low-opportunity counties. Column 5 shows that when including all treatments simultaneously, urbanicity (0.20 fewer children) and land value (0.23 fewer children) effects persist, though with varying significance levels.

Table 8 displays results from equation 3 (columns 1-4) and equation 4 (column 5) with a binary indicator for farming in adulthood as the outcome variable across our four treatment definitions. The table structure remains the same as previous tables. Panel A displays results for the first generation and Panel B for the second generation.

The estimates in Panel A indicate that first-generation riders placed in more developed, wealthier, and more populous areas are significantly less likely to farm in adulthood for the urbanicity (10.5 percentage points), land value (8.1 percentage points), and population (9.1 percentage points) treatment definitions. The literacy treatment definition shows no statistically significant effect of place on farming in adulthood. Column 5 shows that when including all treatments simultaneously, urbanicity (7.7 percentage points), land value at 10% level (4.5 percentage points), and population (4.6 percentage points) all remain significant. The estimates in Panel B demonstrate that second-generation individuals in high-opportunity areas are similarly less likely to farm in adulthood for the urbanicity (11.3 percentage points), land value (11.4 percentage points), and population (7.8 percentage points) treatment definitions. As with the first generation, we find no statistically significant effect on farming in adulthood using our literacy treatment definition . Column 5 shows that when including all treatments simultaneously, urbanicity (7.6 percentage points) and land value (7.9 percentage points) remain significant, while population loses statistical significance.

5.3 Heterogeneity

5.3.1 Does Placement Age Determine Lifetime Outcomes?

Chyn (2018) and Chetty et al. (2016) note that an essential feature of the effects of neighborhoods is an "exposure" effect, place effects on income are concentrated among younger children and increase in intensity with a longer duration in a better neighborhood. We extend the findings from this literature by developing a simple model of human capital formation in our setting.

Consider that average income earned during adulthood is a function of accumulated human capital:

$$Y_i = \omega(HC_i) \tag{5}$$

where $\omega(\cdot)$ is a strictly increasing concave function to reflect diminishing marginal returns to human capital investment (Ben-Porath, 1967).

Human capital for a rider i can be determined by two sequential treatments:

$$HC_i = HC_0 + \Delta_1 Young_i + \Delta_2 T_i + \Delta_3 Young_i \times T_i \tag{6}$$

where HC_0 is baseline human capital for orphaned children in NYC during sample period. Δ_1 is the additional human capital accumulated from being placed at a young age. $Young_i \in \{0, 1\}$ is a binary indicator if a child i was placed at a young age (below 13 from Chyn (2018)) or not. Δ_2 is the additional human capital accumulated from being placed in a high-opportunity county. $T_i \in \{0, 1\}$ is a binary indicator if a child i was placed in a county with at least 3 above-median values for high-opportunity treatment characteristics or not. Δ_3 is the additional human capital acquired by the interaction of being placed young and in a high-opportunity area.

Children are placed out based on their relative arrival to the orphanage. We assume that placement through the orphan train resulted in, on average, higher levels of human capital development than if children remained in NYC, therefore $\Delta_1 > 0$. We can estimate the treatment effects of being placed in higher opportunity and lower opportunity counties for younger and older riders as follows:

$$\tau_{young} = \underbrace{\omega(HC_0 + \Delta_1 + \Delta_2 + \Delta_3)}_{\text{high-opportunity county}} - \underbrace{\omega(HC_0 + \Delta_1)}_{\text{low-opportunity county}} \tag{7}$$

for young riders, and

$$\tau_{old} = \underbrace{\omega(HC_0 + \Delta_2)}_{\text{high-opportunity county}} - \underbrace{\omega(HC_0)}_{\text{low-opportunity county}} \tag{8}$$

for old riders. as $f(\cdot)$ is a strictly increasing concave function, we expect $\tau_{old} > \tau_{young}$. Intuitively, we expect the marginal returns for a higher opportunity place among younger children, $\Delta_2 + \Delta_3$, be relatively less than that of older children, Δ_2, as their accumulation of human capital is larger from the earlier placement during the orphan train movement. We demonstrate this relationship in a simple visualization in Figure 2

Our theoretical framework provides an important dynamic to our setting. While MTO studies find that younger children benefit more from better neighborhoods, our setting allows us to examine how place effects interact with the placement procedure itself. While younger riders receive larger human capital gains when placed in high versus low-opportunity counties compared to older riders ($\Delta_2 + \Delta_3 > \Delta_2$), the marginal income effects are relatively smaller ($\tau_{young} < \tau_{old}$). This occurs because younger riders already possess higher human capital from the orphan train placement itself (Δ_1), and experience diminishing marginal returns. This extends the MTO findings of the "exposure effect" by demonstrating how family formation and neighborhood effects can interact in ways that are challenging to study in modern settings. Our results suggest different baseline human capital accumulation generates heterogeneous marginal effects of place-based opportunities. This implies that early childhood interventions may reduce the relative impact of subsequent investments aimed at children's environment.

To test this model empirically we estimate the following regressions:

$$Y_{ico} = \alpha + \tau_1 Young_i + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{9}$$

and

$$Y_{ico} = \alpha + \tau_1 T_{ic} + \tau_2 Young_i + \tau_3 (T_{ic} \times Young_i) + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{10}$$

where Y_{ico} is the outcome of interest for individual i placed in county c from orphanage o; $T_{ic}$is an indicator for being placed in a high-opportunity county (3 or 4 above median characteristics); and $Young_i$ is an indicator for being placed at age 12 or younger. Our coefficients of interest from equation 9 and equation 10 are τ_1 and τ_3 respectively.

Table 9 displays the results of our estimation of how place effects vary by placement age. The table displays results across three outcomes: occupational income score (columns 1-2), fertility (columns 3-4), and farming propensity (columns 5-6). Columns 1, 3, and 5 show the effect of being placed young (under 13) without conditioning on treatment, while columns 2, 4, and 6 show the full specification including high treatment, young indicator, and their interaction. All specifications include demographic controls and orphanage-by-placement-year fixed effects.

Column 1 shows that younger riders have higher occupational income scores overall (1.91 percentile points). Column 2 includes the full interaction model, revealing that high-opportunity placement increases income (7.29 percentile points), younger riders have higher baseline income (1.13 percentile points), but the interaction term is negative and significant (0.33 percentile points). This indicates that younger riders experience smaller marginal gains from high-opportunity placement compared to older riders, consistent with our theoretical prediction of diminishing marginal returns.

For fertility in columns 3 and 4, column 3 shows no significant baseline difference between younger and older riders. Column 4 reveals that high-opportunity placement reduces fertility (0.47 fewer children), with no significant age heterogeneity in this effect.

For farming in columns 5 and 6, column 5 shows that younger riders are significantly less likely to farm (5.6 percentage points). Column 6 shows that high-opportunity placement substantially reduces farming propensity (16.0 percentage points), younger riders remain less likely to farm at baseline (4.7 percentage points), and the interaction term is positive and marginally significant at the 10% level (0.4 percentage points), suggesting the farming effect of place is slightly smaller for younger riders.

5.3.2 Gender Differences in the Effects of Place

We examine whether the effects of destination characteristics vary by gender. To test for heterogeneous effects, we estimate equation (11) separately by gender and equation (12) with gender interactions:

$$Y_{ico} = \alpha + \tau_1 Female_i + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{11}$$

and

$$Y_{ico} = \alpha + \tau_1 T_{ic} + \tau_2 Female_i + \tau_3 (T_{ic} \times Female_i) + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{12}$$

where $Female_i$ is an indicator equal to one if the child is female, and all other variables are defined as before.

Table 10 displays results across three outcomes: occupational income score (columns 1-2), fertility (columns 3-4), and farming propensity (columns 5-6). Columns 1, 3, and 5 show the effect of being female without conditioning on treatment, while columns 2, 4, and 6 show the full specification including high treatment, female indicator, and their interaction. All specifications include demographic controls and orphanage-by-placement-year fixed effects.

Column 1 shows that girls earn 82% less than men on average for their lifetime occupational income. Column 2 reveals that high-opportunity placement increases income (2.83 percentile points), girls have significantly lower baseline income (43.8 percentile points), but the interaction term is not significant. This indicates that girls and boys experience similar marginal gains from high-opportunity placement despite large baseline differences. For fertility in column 4, high-opportunity placement reduces fertility at the 10% level (0.18 fewer children), with no significant gender heterogeneity in this effect. Column 5 reveals girls are less likely to work in agriculture at baseline (7.5 percentage points) irrespective of treatment. For farming in column 6, high-opportunity placement substantially reduces farming propensity (6.9 percentage points), girls are less likely to farm at baseline (6.3 percentage points), and the interaction term is not significant, suggesting the farming effect of place is similar across genders.

5.3.3 Differences in Place Effects in Earlier and Later Years

We examine whether the effects of destination characteristics vary by placement period. To test for heterogeneous effects, we estimate equation (13) separately by time period and equation (14) with time period interactions:

$$Y_{ico} = \alpha + \tau_1 Early_i + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{13}$$

and

$$Y_{ico} = \alpha + \tau_1 T_{ic} + \tau_2 Early_i + \tau_3 (T_{ic} \times Early_i) + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{14}$$

where $Early_i$ is an indicator equal to one if the child was placed before 1890, and all other variables are defined as before. Note that these specifications do not include placement year fixed effects, as the early indicator would be perfectly collinear with these controls.

Table 11 displays results across three outcomes: occupational income score (columns 1-2), fertility (columns 3-4), and farming propensity (columns 5-6). Columns 1, 3, and 5 show the effect of being placed early without conditioning on treatment, while columns 2, 4, and 6 show the full specification including high treatment, early indicator, and their interaction. All specifications include demographic controls and orphanage fixed effects.

Column 1 shows that children placed before 1890 have significantly lower occupational income scores (5.77 percentile points). Column 2 reveals that high-opportunity placement increases income (4.27 percentile points), early riders have lower baseline income (3.60 percentile points), but the interaction term is not significant. This indicates that children placed in different time periods experience similar marginal gains from high-opportunity placement. For fertility in column 4, high-opportunity placement reduces fertility (0.30 fewer children), early riders have higher baseline fertility (0.39 more children), with no significant time period heterogeneity in the treatment effect. Column 5 reveals children placed before 1890 are more likely to work in agriculture at baseline (10.5 percentage points) irrespective of treatment. For farming in column 6, high-opportunity placement substantially reduces farming propensity (14.5 percentage points), but low-opportunity early riders are not more likely to farm at baseline and the interaction term is not significant, suggesting the farming effect of place is similar across time periods.

5.3.4 Geographic Variation in Place

Alternative specifications of place may reveal different mechanisms driving our results. One possibility is that county-level differences across median characteristic levels are primarily capturing broader regional variation. To test this, we examine geographic variation as a robustness check while exploring potential regional mechanisms driving place effects. We estimate a similar equation as before, but replace county-level characteristic treatment with an indicator for being in one of 5 census regions: New England, East Midwest, West Midwest, South, and West.[25]

Specifically, we define the empirical design as follows:

$$Y_{ico} = \alpha + \sum_{j=1}^{5} \eta_j L_{ij} + X_i'\beta + \gamma_{co} + \epsilon_{ico} \tag{15}$$

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).

To assess whether regional treatment assignment is balanced, we present regression balance tests in Table A.7. The table shows that while some demographic characteristics differ across regions—notably placement age and race these differences are economically small. Table A.8 presents normalized differences in pairwise region comparisons, confirming that demographic characteristics are broadly balanced across regional treatments.

In Table 12, we present the results of this regional analysis for our main outcomes. Specifically, the table displays coefficients for four different outcomes: occupational income score for first generation riders (column 1), occupational income score for second generation riders (column 2), fertility for first generation riders (column 3), and fertility for second generation riders (column 4). Each row represents a different region—East Midwest, New England, South, West, and West Midwest—with Mid-Atlantic as the omitted comparison

[25] See Figure A.6 for visualization of classification

region. For each region-outcome combination, we report the coefficient estimate and standard error (in parentheses).

The estimates in Panel A column 1 indicate that there are no regional differences with respect to average lifetime occupational income in the first generation with the exception for the East Midwest resulting in less occupational income score (4.90 percentile points), with all other coefficients statistically insignificant relative to the Mid-Atlantic. The estimates in column 2 show significant regional variation in fertility, with children placed in the East Midwest, South, and West Midwest having 0.98 to 1.54 more children compared to the Mid-Atlantic region. For farming propensity in column 3, children placed in the East Midwest, South, and West Midwest are 19.4 to 29.8 percentage points more likely to farm than those in the Mid-Atlantic, with the South showing the largest effect (22.9 percentage points).

The estimates in Panel B reveal greater regional heterogeneity in the second generation. Column 1 shows that second generation children in the South and West Midwest have significantly lower occupational income scores (-10.5 and -8.7 percentile points respectively) compared to the Mid-Atlantic. Column 2 indicates second generation fertility effects are positive for the South (1.34 more children) and East Midwest (0.54 more children) but not significant for other regions. Column 3 shows second generation farming propensity remains elevated in the West (47.1 percentage points) and West Midwest (18.7 percentage points) relative to the Mid-Atlantic.

Overall, our regional analysis provides an alternative examination of the effect of place on socioeconomic outcomes and their intergenerational transmissions. These regional patterns indicate that the county-level opportunity effects capture meaningful local variation beyond broader regional differences, as regional coefficients show different patterns than our county-level treatment effects. The strong farming effects in agricultural regions (South, West Midwest, and East Midwest) and varying income and fertility effects across regions suggest that local economic structure matters for understanding place-based outcomes.

6 Mechanisms

Having established that placement in high-opportunity locations affected rider outcomes, we now investigate two key mechanisms underlying these effects: the relative importance of household versus place characteristics, and the role of migration in the intergenerational persistence of place effects.

6.1 The Effects of the Household

A central challenge in estimating place effects is disentangling the influence of neighborhoods from household-level characteristics. Families typically move together, making it difficult to separate these influences. The Orphan Train Movement provides a unique opportunity to address this challenge: children were placed into existing households in their destination counties, allowing us to observe both the macro-level environment (county characteristics) and the micro-level environment (household quality) independently.

We estimate the relative importance of these two channels by including both our place-based opportunity index and a measure of household quality which we define as the father's occupational income score percentile rank at the time nearest to placement. For the second generation, the household measure captures the rider's own occupational income score at the riders original placement age, effectively estimating the intergenerational elasticity (IGE) of income (Cholli & Durlauf, 2022). The specification takes the form:

$$Y_{ico} = \alpha + \tau_1 OpportunityIndex_i + \tau_2 HouseholdOccScore_i + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{16}$$

where we include both the opportunity index and household occupation score simultaneously to decompose the total effect of placement into household versus place components. Table 13 presents the decomposition results. Panel A shows first generation riders and Panel B shows second generation descendants. The table displays results across three outcomes: occupational income score (columns 1-2), fertility (columns 3-4), and farming propensity (columns 5-6). Odd columns show the opportunity index effect without household controls, while even columns include both opportunity index and household occupation score. The results reveal that household characteristics matter substantially. In Panel A column 2, a one percentile point increase in foster household occupation score raises rider income by 0.147 percentile points, while the opportunity index coefficient is 0.815 percentile points per standard deviation. To compare magnitudes on equal footing, we calculate standardized effects using the standard deviations from the estimation sample. A one standard deviation increase in place opportunity (SD = 1.29) raises income by 1.05 percentile points, while a one standard deviation increase in foster household quality (SD = 34.97) raises income by 5.15 percentile points. Foster household quality has an effect approximately 5 times larger than place for income outcomes. This household dominance extends to other outcomes. For fertility in Panel A column 4, household effects are 1.5 times larger than place effects and place effects are insignificant after controlling for household effects. For farming in Panel A column 6, household effects are 3.7 times larger. Notably, the place effects remain significant for occupational income scores at the 10% level and farming even after controlling for household characteristics, indicating that both the micro-level (household) and macro-level (county) environments independently shape outcomes. Panel B shows that these patterns persist into the second generation. The household occupation score now reflects the parent's (Gen 1) income, providing an estimate of intergenerational elasticity. Column 2 reveals an IGE of 0.175 which is lower than modern estimates of approximately 0.34 (Chetty et al., 2014), suggesting relatively high intergenerational mobility despite the extreme childhood disruption experienced by orphan train riders. Importantly, both household and place effects strengthen in the second generation: the household coefficient increases from 0.147 to 0.175, while the opportunity index coefficient increases from 0.815 to 1.108. This strengthening of both channels is consistent with riders in high-opportunity locations developing greater human capital and providing more stable family environments that they subsequently transmit to their children, regardless of where those children ultimately live. Unlike Gen 1 riders who experienced childhood disruption through placement, Gen 2 children benefit from intact families shaped by their parents' experiences in better households and locations. The ratio of household to place effects remains large at 4.4 times for income, though place effects continue to operate independently. [26]

6.2 Adulthood Migration

A natural concern is whether the intergenerational effects documented in Section 5 operate through direct geographic persistence by children simply remaining in their parents' placement locations, if it helps them select other high-opportunity localities, or if the transmission is occurring through shaping the individual irrespective of their next location. If second generation children predominantly stay in their parents' placement counties, the observed intergenerational effects might reflect continued exposure to the same local environment rather than transmission of human capital or characteristics developed during the rider's formative years.

We investigate this mechanism by examining migration patterns among riders and their descendants. The specification takes the form:

$$M_{ico} = \alpha + \delta_1 OpportunityIndex_i + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{17}$$

where M_{ico} represents various migration outcomes. For Table 14, these include whether the rider remained in their placement county during prime working years, the number of lifetime county moves, age at first move, and the opportunity level of destination counties for movers. For Table 15, outcomes are staying in placement state, leaving both county and state, and returning to New York."

We investigate this mechanism by examining migration patterns among riders and their

[26]Tables A.9, A.10, and A.11 in the appendix explore how individual treatment components (literacy, urbanicity/residential development, land value, and population) contribute to the overall opportunity index effects while controlling for household characteristics. The patterns largely mirror the combined treatment results, with household effects remaining the dominant mechanism across all specifications.

descendants. Table 14 presents the relationship between placement opportunity and subsequent migration behavior. Column 1 examines whether riders remained in their placement county during prime working years (ages 25-54).[27] Riders placed in high-opportunity counties were 2.2 percentage points more likely to remain in their placement county, statistically significant effect at the 10% level. This represents approximately a 10% increase over the baseline rate of 22.6%, suggesting that opportunity creates weak place attachment even in this high-mobility historical era.

Column 2 examines the total number of lifetime county moves. Higher placement opportunity is associated with 0.046 fewer moves, significant at the 10% level which translates to a 4% reduction from the mean of 1.15 moves. While marginally significant, this result reinforces the narrative of reduced mobility in high-opportunity locations. Column 3 finds no significant relationship between placement opportunity and age at first move, indicating that opportunity affects whether people move, not when. Column 4 examines if riders who move systematically sort into destinations of similar opportunity quality. We restrict the sample to movers whose adult counties also received rider placements, allowing us to measure destination opportunity using the same construction as placement opportunity. The coefficient is small (0.044) and statistically insignificant, indicating that migration decisions were driven by factors orthogonal to measured economic opportunity.

Table 15 explores the geographic scope of migration patterns. Column 1 shows that placement opportunity has no significant effect on whether riders stayed in their placement state. Column 2 reveals that riders in high-opportunity locations were 3.0 percentage points less likely to leave their placement county and state simultaneously. This suggests high-opportunity placements created some local attachment that reduced long-distance migration. Columns 3 and 4 examine return migration to New York, finding no significant relationship between placement opportunity and the likelihood of returning to either New York State or

[27] Tables A.12 and A.13 in the appendix examine migration patterns across the full age distribution rather than restricting to prime working years. These specifications yield slightly different results, potentially capturing different types of migration unrelated to economic opportunity, such as moves for retirement, health concerns, or family caregiving in later life.

New York City. This indicates that the the majority (98%) of riders never returned to their home state.

These migration patterns have important implications for interpreting our intergenerational results. While high-opportunity placements created modest place attachment among first-generation riders, geographic mobility remained high as approximately 77% of riders left their placement county by prime working years. More critically, among second generation children, geographic persistence in their parents' placement counties was even lower. This high mobility rate suggests that the intergenerational effects documented in Section 5 must operate primarily through characteristics or human capital transmitted by parents during formative years, rather than through simple geographic co-location in the same high-opportunity environment. The strengthening of place effects across generations occurs despite the majority of second generation children living in different locations than their parents' placement counties, supporting a mechanism of human capital transmission rather than continued environmental exposure.

7 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 to improve long-term mobility outcomes. We find that riders who were placed in populous, more residentially developed counties had higher occupational income scores. This likely reflects the role that access to larger labor markets plays in upward mobility.

This finding aligns with recent work by Chetty and Hendren (2018a), who find that exposure to better neighborhoods during childhood leads to improved adult outcomes. Our results extend the Moving to Opportunities literature by demonstrating that these effects persist across generations. This intergenerational persistence of income, fertility, and occupational type outcomes highlights the importance of addressing place-based inequalities early in life. The benefits of living in a place with favorable characteristics 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. Our results may indicate that pursuing economic success may come at the cost of lifetime fertility. Policies that help mitigate these trade-offs could promote both economic and demographic well-being.

There are several important considerations when interpreting our results. First, the Orphan Train Movement is an extremely novel event. The results of our paper are consistent with potential mechanisms identified in other work, however, specific estimates may lack external validity due to the uniqueness of the policy relative to modern-day analogues. Second, place can be characterized through a variety of approaches. It is crucial to interpret these results under the correct treatment definitions. Finally, we hope that future work will seek to disentangle additional heterogeneity among subgroups of riders, potential yielding additional insights that are obfuscated by high-level analysis.

8 Conclusion

Here's a revised conclusion that matches the intro's style - more direct and less contrived:

7. Conclusion We provide causal evidence on how place shapes long-term and intergenerational socioeconomic outcomes by examining the Orphan Train Movement, which relocated 300,000 displaced and orphaned children from New York City to families throughout the United States between 1853 and 1929. By leveraging the quasi-random placement of children based on institutional capacity constraints and arrival timing at orphanages, we avoid

selection bias inherent in typical place-based studies.

We define place at the county level using four key characteristics measured at the time of placement: literacy rates, urbanicity, land value, and population. Using an opportunity index that aggregates across these dimensions, we find that riders placed in high-opportunity counties earn 1.15 percentile points more in occupational income scores, have 0.09 fewer children, and are 4.4 percentage points less likely to work in agriculture compared to riders in low-opportunity counties. These effects persist and amplify in the second generation with income gains of 1.24 percentile points, fertility reductions of 0.13 children, and farming reductions of 4.3 percentage points.

Examining each dimension separately reveals which features of opportunity drive these results. Urbanicity generates the largest income gains (2.42 percentile points for first generation, 2.92 for second generation) and reduces farming propensity by approximately 10-11 percentage points across both generations. Land value and population size also significantly increase income across both generations, while literacy shows no effects on occupational income. These patterns demonstrate that residential development, wealth, and labor market size matter substantially for long-run earnings, while education access measured through literacy does not.

A central contribution of our analysis is decomposing place effects into household versus county-level components. Household characteristics generate effects approximately five times larger than county-level place characteristics for occupational income, with similar magnitudes for fertility and farming outcomes. Both household and place effects strengthen across generations despite high geographic mobility with 77% of riders left their placement counties by prime working years. This indicates that intergenerational persistence operates through human capital transmission and family environments rather than continued environmental exposure. The estimated intergenerational elasticity of 0.175 indicates substantially higher income mobility in this historical context compared to modern estimates of 0.34.

Our findings extend the place effects literature in several ways. First, we provide causal evidence on which dimensions of place drive long-run economic outcomes beyond neighborhood poverty rates, demonstrating that urbanization, wealth, and labor market size matter substantially while local literacy shows no effects. Second, we study placements across diverse geographic contexts including rural areas, providing evidence that place effects operate beyond typical urban settings. Third, we provide the first causal evidence of intergenerational transmission of place effects, showing benefits extend to children with effects that persist or amplify across generations. Finally, our decomposition of household versus place effects addresses a fundamental identification challenge, showing that while household-level factors dominate, macro-level environments persist as independent factors. These results inform contemporary policy discussions on child welfare, place-based interventions, and the mechanisms underlying intergenerational mobility.

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Tables and Figures

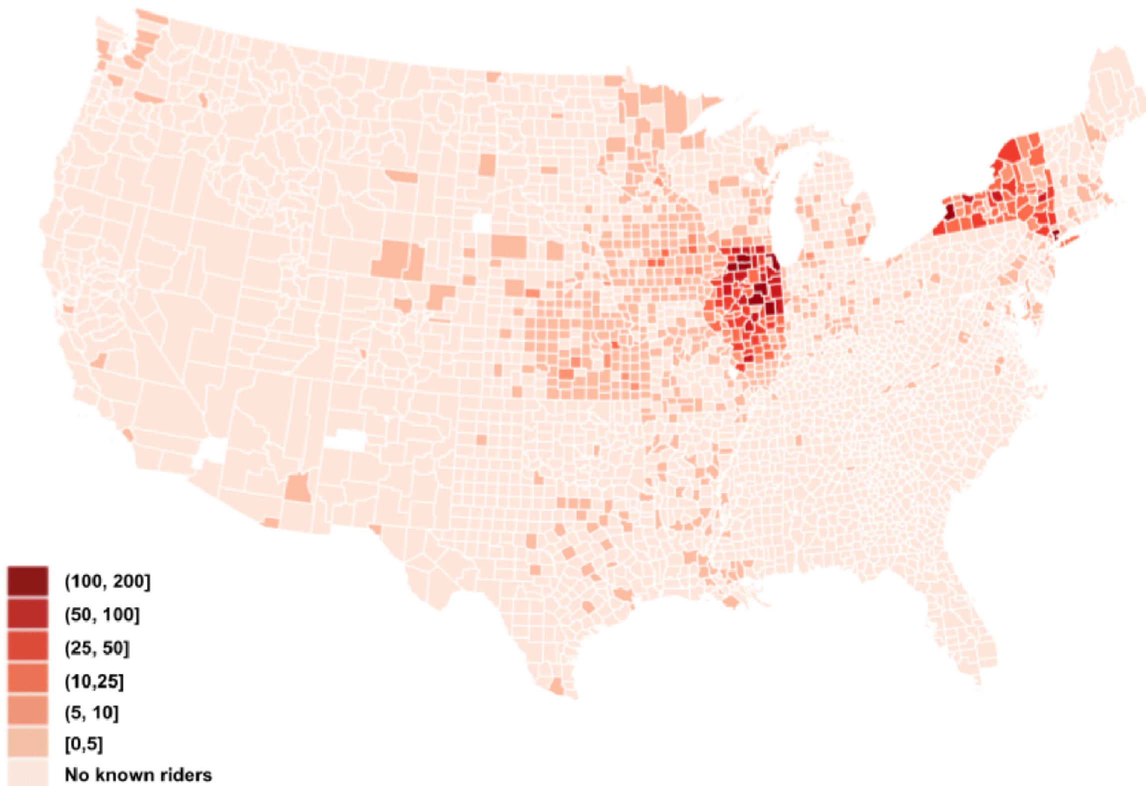


Figure 1: Distribution of Riders by Destination County

Notes: Figure plots the geospatial distribution of rider destination locations across the United States, at the county level. The "No known riders" classification includes counties that we do not observe receiving an Orphan Train rider in our data. However, because we do not have the full universe of all Orphan Train riders, we classify these counties as having no known riders.

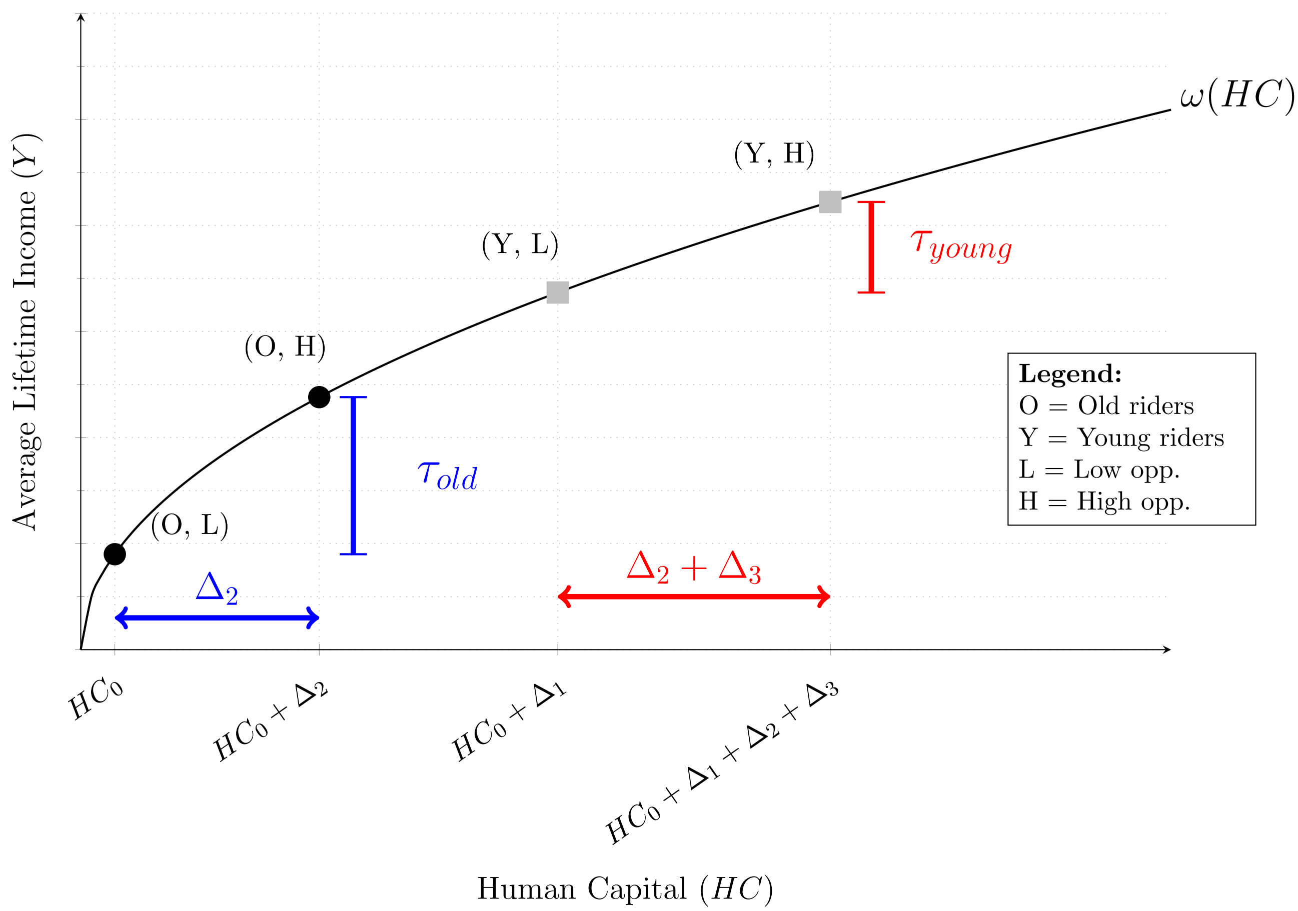


Figure 2: Visualization of Age Heterogeneity Effects

Notes: This figure illustrates the theoretical framework for age heterogeneity in place effects. The concave function $\omega(HC)$ maps human capital to average lifetime income, reflecting diminishing marginal returns. The four points represent combinations of rider age and placement opportunity: (O, L) = old rider in low-opportunity county with baseline human capital HC_0; (O, H) = old rider in high-opportunity county with human capital $HC_0 + \Delta_2$; (Y, L) = young rider in low-opportunity county with human capital $HC_0 + \Delta_1$; (Y, H) = young rider in high-opportunity county with human capital $HC_0 + \Delta_1 + \Delta_2 + \Delta_3$. Here Δ_1 represents additional human capital from early placement, Δ_2 represents human capital gains from high-opportunity locations, and Δ_3 captures the interaction between young age and high-opportunity placement. The horizontal arrows show human capital differences: old riders gain Δ_2 from better places, while young riders gain $\Delta_2 + \Delta_3$. The vertical brackets show income effects: τ_{old} (blue) measures the income gain for old riders from better places, while τ_{young} (red) measures the same for young riders. Due to the concavity of $\omega(\cdot)$, even though young riders accumulate more human capital from better places ($\Delta_2 + \Delta_3 > \Delta_2$), they experience smaller marginal income gains ($\tau_{young} < \tau_{old}$) because they start from a higher baseline due to early placement benefits (Δ_1).

Table 1: Data Cleaning Process Statistics

	AFGS	CAS	NOTC	NYJA	Fraction Kept
Digitized Records	1,443	3,342	3,132	10,371	1
Census Links ≥ 1	1,095	1,827	1,384	6,746	0.604
Census Links ≥ 2	826	1,424	1,134	5,454	0.800
All Outcomes Present	739	1,155	489	4,632	0.794
All Controls Present	334	782	473	4,568	0.878
Verified Rider	238	357	471	2,429	0.568

Notes: This table reports the number of observations at each step in the data linking and cleaning process for each of the four orphanage groups in our data: American Female Guardian Society (AFGS), Children's Aid Society (CAS), National Orphan Train Complex (NOTC), and New York Juvenile Asylum (NYJA). The "Fraction Kept" column reports the fraction of observations from the previous step in the process were were retained in the data after the current step in the process occurred. Row 1 reports the total number of unique individuals with digitized records for each orphanage in the data. Row 2 reports the number of individuals linked to at least 1 full-count U.S. Census. Row 3 reports the number of individuals linked to at least 2 full-count U.S. Censuses. Row 4 reports the number of individuals for whom we can measure all outcomes analyzed in Tables 4 through 6. Row 5 reports the number of individuals who have all observable control variables used in our main analyses. "Verified Rider" reports the number of individuals who we verify as Orphan Train riders based on our primary data sources (i.e. orphanage records).

Table 2: Summary Statistics at Each Stage of Data Cleaning Process

	Female	White	Placement Age	Native	Observations
Census Links ≥ 1	0.262	0.976	12.79	0.822	9,622
	(0.440)	(0.152)	(4.63)	(0.382)	
Census Links ≥ 2	0.244	0.982	13.12	0.840	7,787
	(0.429)	(0.132)	(4.58)	(0.366)	
All Outcomes Present	0.227	0.985	13.21	0.829	7,015
	(0.419)	(0.121)	(4.57)	(0.377)	
All Controls Present	0.217	0.984	13.21	0.836	6,157
	(0.412)	(0.126)	(4.47)	(0.371)	
Verified Rider	0.254	0.989	13.12	0.850	3,495
	(0.436)	(0.105)	(4.76)	(0.357)	

Notes: This table reports the observable comparability of the analysis sample at each stage of the data cleaning process, starting with the sample we linked to at least 1 historical Census in row 1. Row 2 reports summary statistics for individuals that linked to two Censuses, row 3 further restricts the sample to individuals for whom we can measure all outcomes analyzed in Tables 4 through 6. Row 4 further restricts the sample to individuals who have all observable control variables present. Row 5 restricts the sample to only individuals who are verified as Orphan Train riders based on our primary data sources (i.e. orphanage records). Means are reported for four observable characteristics: sex, race, age of first placement, and native birth status for columns 1 through 4, respectively. Column 5 reports the sample size for each stage. Standard deviations in brackets.

Table 3: Balance of Baseline Characteristics Across Opportunity Levels

	Low Treatment (0-1)	High Treatment (3-4)	Difference
Female	0.261	0.250	0.011
			(0.019)
White	0.994	0.985	0.009
			(0.005)
Placement Age	12.566	12.872	-0.306
			(0.186)
Native	0.858	0.823	0.035**
			(0.016)

Notes: Reports mean characteristics and differences between low (0-1) and high (3-4) opportunity treatment groups. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Regression Balance Tests for Opportunity Index

	Full Sample	Native-Born Only
	(1)	(2)
Female	0.054	0.070*
	(0.038)	(0.042)
White	0.228	0.224
	(0.144)	(0.149)
Placement Age	0.004	0.006
	(0.004)	(0.005)
Native	-0.124**	
	(0.060)	
Observations	3,484	2,959
F-statistic	2.41	2.13
P-value	0.048	0.094

Notes: County-census year level clustered standard errors in parentheses. Dependent variable is the opportunity index (0-4). Both columns include orphanage-by-placement-year fixed effects. F-statistic and p-value test joint significance of all covariates. Standard errors clustered at county-census year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects of Total Treatment on Outcomes

	Avg Income		Number of Children		Ever Farmer	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First Generation						
Opportunity Index	1.149***		-0.089**		-0.044***	
	(0.362)		(0.040)		(0.009)	
Low Opportunity		-0.390		-0.060		-0.003
(*Treat=1*)		(1.091)		(0.116)		(0.024)
Medium Opportunity		-0.334		-0.037		-0.051*
(*Treat=2*)		(1.186)		(0.128)		(0.029)
High Opportunity		1.431		-0.273**		-0.110***
(*Treat=3*)		(1.323)		(0.124)		(0.034)
V. High Opportunity		5.702***		-0.330		-0.167***
(*Treat=4*)		(1.593)		(0.209)		(0.039)
Observations	3,484	3,484	3,484	3,484	3,484	3,484
V. Low Opp. Mean	40.224	40.224	2.825	2.825	0.518	0.518
(*Treat=0*)						
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Second Generation						
Opportunity Index	1.240**		-0.130***		-0.043***	
	(0.498)		(0.034)		(0.012)	
Low Opportunity		0.669		-0.185		-0.020
(*Treat=1*)		(1.598)		(0.125)		(0.039)
Medium Opportunity		1.171		-0.187		-0.060
(*Treat=2*)		(1.748)		(0.143)		(0.039)
High Opportunity		4.673***		-0.456***		-0.159***
(*Treat=3*)		(1.783)		(0.147)		(0.042)
V. High Opportunity		3.162		-0.490***		-0.108**
(*Treat=4*)		(2.041)		(0.145)		(0.053)
Observations	3,059	3,059	3,059	3,059	3,059	3,059
V. Low Opp. Mean	42.303	42.303	2.001	2.001	0.400	0.400
(*Treat=0*)						
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the effects of the opportunity index on three main outcomes. Columns (1), (3), and (5) show linear specifications where total treatment ranges from 0-4. Columns (2), (4), and (6) show dummy specifications with separate indicators for each opportunity treatment level. The omitted category is opportunity index = 0 or very low-opportunity treatment. Opportunity treatments are classified by the number of above median treatments for literacy, residential development, land value, and population. The number of counties in each opportunity treatment for the first generation are as follows: very low-opportunity treatment = 635, low-opportunity treatment = 977, medium opportunity treatment = 713, high-opportunity treatment = 772, and very high-opportunity = 389. The number of counties in each opportunity treatment for the second generation are as follows: very low-opportunity treatment = 554, low-opportunity treatment = 804, medium opportunity treatment = 736, high-opportunity treatment = 713, and very high-opportunity = 252. Demographic controls include gender, age, race, and immigrant status. Orphanage-placement year fixed effects are included in all regressions. Standard errors are clustered at the county-census year level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of Place on Average Income

	Average Occupational Income Score				
	(1)	(2)	(3)	(4)	(5)
Panel A: First Generation					
Literacy	0.007				0.251
	(0.776)				(0.810)
Urbanicity		2.419***			1.776***
		(0.785)			(0.866)
Land Value			1.713*		0.752
			(0.933)		(0.941)
Population				2.237**	1.397
				(0.912)	(0.976)
Observations	3,484	3,484	3,484	3,484	3,484
Low-opportunity Mean	50.66	40.93	41.29	40.96	40.224
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Second Generation					
Literacy	-1.181				-0.774
	(1.214)				(1.159)
Urbanicity		2.921**			1.567
		(1.174)			(1.222)
Land Value			3.826***		2.839*
			(1.403)		(1.594)
Population				2.431**	0.386
				(1.219)	(1.315)
Observations	3,194	3,194	3,194	3,194	3,059
Low-opportunity Mean	48.01	43.58	43.32	43.05	42.303
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Each column between 1-4 is a separate regression for each of the four county-level treatments outlined in Section 4: literacy, urbanicity, average land value, and population. The fifth column represents the "horse-race" specification outlined in Section 4. Panel A reports results of the effect of each treatment on average prime-age (25-54) occupational income 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-placement year fixed effects are included in all regressions. Standard errors are clustered at the county-census year level and displayed in parentheses. Horse race specification has a slightly smaller sample in the second generation because the fixed effects require variation across all treatments within orphanage-years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effects of Place on Fertility

	Number of Children				
	(1)	(2)	(3)	(4)	(5)
Panel A: First Generation					
Literacy	-0.014				-0.050
	(0.088)				(0.093)
Urbanicity		-0.157*			-0.089
		(0.081)			(0.089)
Land Value			-0.077		0.015
			(0.101)		(0.100)
Population				-0.244***	-0.221**
				(0.093)	(0.099)
Observations	3,484	3,484	3,484	3,484	3,484
Low-opportunity Mean	2.183	2.662	2.649	2.664	2.825
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Second Generation					
Literacy	0.059				0.022
	(0.077)				(0.070)
Urbanicity		-0.296***			-0.203***
		(0.074)			(0.069)
Land Value			-0.322***		-0.230***
			(0.089)		(0.087)
Population				-0.223***	-0.034
				(0.084)	(0.079)
Observations	3,194	3,194	3,194	3,194	3,059
Low-opportunity Mean	1.627	1.900	1.906	1.880	2.001
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Each column between 1-4 is a separate regression for each of the four county-level treatments outlined in Section 4: literacy, urbanicity, average land value, and population. The fifth column represents the "horse-race" specification outlined in Section 4. Panel A reports results of the effect of each treatment on total number of children for the 1st generation (Orphan Train riders). 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-placement year fixed effects are included in all regressions. Standard errors are clustered at the county-census year level and displayed in parentheses. Horse race specification has a slightly smaller sample in the second generation because the fixed effects require variation across all treatments within orphanage-years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effects of Place on Farming Occupation

	Ever Worked in Farming				
	(1)	(2)	(3)	(4)	(5)
Panel A: First Generation					
Literacy	0.029				0.021
	(0.020)				(0.019)
Urbanicity		-0.105***			-0.077***
		(0.021)			(0.021)
Land Value			-0.081***		-0.045*
			(0.027)		(0.024)
Population				-0.091***	-0.046**
				(0.023)	(0.022)
Observations	3,484	3,484	3,484	3,484	3,484
Low-opportunity Mean	0.255	0.520	0.501	0.507	0.518
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Second Generation					
Literacy	0.036				0.022
	(0.028)				(0.027)
Urbanicity		-0.113***			-0.076***
		(0.026)			(0.025)
Land Value			-0.114***		-0.079***
			(0.031)		(0.029)
Population				-0.078***	-0.008
				(0.028)	(0.026)
Observations	3,194	3,194	3,194	3,194	3,059
Low-opportunity Mean	0.243	0.380	0.375	0.372	0.400
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Each column between 1-4 is a separate regression for each of the four county-level treatments outlined in Section 4: literacy, urbanicity, average land value, and population. The fifth column represents the "horse-race" specification outlined in Section 4. Panel A reports results of the effect of each treatment on whether an individual ever worked in farming as an adult for the 1st generation (Orphan Train riders). Panel B reports results of the effect of each treatment on whether an individual ever worked in farming as an adult for the 2nd generation (children of riders). Demographic controls include gender, age, race, and immigrant status. Orphanage-placement year fixed effects are included in all regressions. Standard errors are clustered at the county-census year level and displayed in parentheses. Horse race specification has a slightly smaller sample in the second generation because the fixed effects require variation across all treatments within orphanage-years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Age Heterogeneity on Place Effects

	Occ. Income Score		Number of Children		Ever Farmer	
	(1)	(2)	(3)	(4)	(5)	(6)
High Treatment		7.288***		-0.468**		-0.160***
		(2.442)		(0.197)		(0.044)
Young (< 13)	1.908**	1.133	-0.046	-0.009	-0.056***	-0.047**
	(0.911)	(0.961)	(0.084)	(0.096)	(0.017)	(0.020)
HighxYoung		-0.333**		0.016		0.004*
		(0.166)		(0.014)		(0.003)
Observations	3,484	3,484	3,484	3,484	3,484	3,484
Control Mean	43.32	40.75	2.474	2.830	0.443	0.505
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports heterogeneous effects of place by placement age. Columns (1) and (2) show average occupational income score effects and age interactions for the opportunity index. Columns (3) and (4) show the effects of place with age heterogeneity on fertility. Columns (5) and (6) show the effects of place with age heterogeneity on ever farming in adulthood. High treatment is characterized as being placed in a county with a score of 3 or 4 for the opportunity index. Young riders are defined as those placed at age 12 or younger. HighxYoung is the interaction between being in a high treatment and being at age 12 or younger. Demographic controls include gender, race, and immigrant status. Orphanage-placement year fixed effects are included in all regressions. Standard errors are clustered at the county-census year level and displayed in parentheses. The omitted group for columns (1), (3), and (5) are riders above the age of 12. The omitted group for columns (2), (4), and (6) are riders above the age of 12 and placed in low treated counties. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Gender Heterogeneity on Place Effects

	Occ. Income Score		Number of Children		Ever Farmer	
	(1)	(2)	(3)	(4)	(5)	(6)
High Treatment		2.825***		-0.181*		-0.093***
		(1.058)		(0.100)		(0.026)
Female	-43.723***	-43.848***	0.103	0.194*	-0.075***	-0.063***
	(0.747)	(0.887)	(0.089)	(0.107)	(0.018)	(0.022)
HighxFemale		0.231		-0.264		-0.030
		(1.615)		(0.177)		(0.037)
Observations	3,484	3,484	3,484	3,484	3,484	3,484
Control Mean	52.83	52.83	2.599	2.599	0.507	0.507
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports heterogeneous effects of place by gender. Columns (1) and (2) show average occupational income score effects and gender interactions for the opportunity index. Columns (3) and (4) show the effects of place with gender heterogeneity on fertility. Columns (5) and (6) show the effects of place with gender heterogeneity on ever farming in adulthood. High treatment is characterized as being placed in a county with a score of 3 or 4 for the opportunity index. HighxGender is the interaction between being in a high treatment and being female. Demographic controls include age, race, and immigrant status. Orphanage-placement year fixed effects are included in all regressions. Standard errors are clustered at the county-census year level and displayed in parentheses. The omitted group for columns (1), (3), and (5) are male riders. The omitted group for columns (2), (4), and (6) are male riders in low treated counties. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Time Heterogeneity on Place Effects

	Occ. Income Score		Number of Children		Ever Farmer	
	(1)	(2)	(3)	(4)	(5)	(6)
High Treatment		4.266**		-0.300**		-0.145***
		(1.717)		(0.150)		(0.037)
Early (< 1890)	-5.767***	-3.601**	0.511***	0.387***	0.105***	0.033
	(1.005)	(1.475)	(0.098)	(0.133)	(0.021)	(0.032)
HighxEarly		-1.577		-0.001		0.045
		(1.990)		(0.183)		(0.046)
Observations	3,495	3,495	3,495	3,495	3,495	3,495
Control Mean	40.81	40.81	2.279	2.279	0.496	0.496
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No

Notes: Each column reports heterogeneous effects of place by placement period. Columns (1) and (2) show average occupational income score effects and time interactions for the opportunity index. Columns (3) and (4) show the effects of place with time heterogeneity on fertility. Columns (5) and (6) show the effects of place with time heterogeneity on ever farming in adulthood. High treatment is characterized as being placed in a county with a score of 3 or 4 for the opportunity index. Early is an indicator =1 if a rider was placed before 1890. HighxEarly is the interaction between being in a high treatment and being in the early placement period. Demographic controls include age, race, and immigrant status. Orphanage fixed effects are included in all regressions. Placement year fixed effects are not included. Standard errors are clustered at the county-census year level and displayed in parentheses. The omitted group for columns (1), (3), and (5) are riders placed during or after 1890. The omitted group for columns (2), (4), and (6) are riders placed during or after 1890 in low treated counties. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Effect of Place by Geography

	Occ. Income Score	Fertility	Farming
	(1)	(2)	(3)
Panel A: First Generation			
East Midwest	-4.895**	0.984***	0.194***
	(2.439)	(0.229)	(0.057)
New England	-7.230	0.961	-0.147
	(7.144)	(0.777)	(0.141)
South	-2.454	1.537***	0.229**
	(4.111)	(0.421)	(0.096)
West	4.535	1.372*	0.093
	(7.300)	(0.740)	(0.167)
West Midwest	-4.791	0.972***	0.298***
	(3.017)	(0.291)	(0.071)
Observations	3,479	3,479	3,479
Mid-Atlantic Mean	55.21	1.893	0.167
Demographic Controls	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes
Panel B: Second Generation			
East Midwest	-3.086	0.537**	0.119*
	(2.655)	(0.214)	(0.061)
New England	-4.565	-0.759	-0.092
	(6.552)	(0.492)	(0.147)
South	-10.490**	1.340***	0.012
	(4.058)	(0.467)	(0.135)
West	-7.079*	-0.618	0.471***
	(4.126)	(0.479)	(0.117)
West Midwest	-8.688***	0.268	0.187**
	(3.124)	(0.261)	(0.084)
Observations	3,059	3,059	3,059
Mid-Atlantic Mean	51.19	1.463	0.166
Demographic Controls	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes

Notes: The outcome in the first two columns is the average prime-age (25-54) occupational income score. The second two columns report effects on total number of children. The final two columns report effects on likelihood of living on a farm. The first, third, and fifth columns report effects for the first generation (Orphan Train riders), while the second, fourth, and sixth columns report effects for the second generation (their children). The omitted category in each regression is the Mid-Atlantic Census region where New York City is located. 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 county-census year level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Effects of Place with Household Characteristics

	Occupational Income Score		Fertility		Farming	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First Generation						
Opportunity Index	1.149***	0.815*	-0.089**	-0.068	-0.044***	-0.037***
	(0.362)	(0.451)	(0.040)	(0.048)	(0.009)	(0.009)
Household Occ. Score		0.147***		-0.008***		-0.005***
		(0.015)		(0.001)		(0.000)
Observations	3,484	2,547	3,484	2,547	3,484	2,547
V. Low. Opp. Mean	43.349	44.141	2.474	2.320	0.445	0.463
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Second Generation						
Opportunity Index	1.942***	1.108**	-0.173***	-0.120***	-0.069***	-0.040***
	(0.535)	(0.527)	(0.035)	(0.033)	(0.015)	(0.012)
Household Occ. Score		0.175***		-0.007***		-0.006***
		(0.017)		(0.001)		(0.000)
Observations	4,268	3,866	4,268	3,866	4,268	3,866
V. Low-Opp Mean	47.599	48.044	1.584	1.576	0.255	0.257
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel A shows first generation riders; Panel B shows second generation of rider descendants. Outcome is occupation income score percentile rank (1-100) in columns (1)-(2), number of children in columns (3)-(4), and indicator for ever being a farmer in columns (5)-(6). Opportunity Index is the standardized place-based treatment. Household Occ. Score is the father's occupational income score percentile rank nearest to placement year for the first generation. For the second generation Household Occ. Score is the father's occupational income score percentile rank nearest to age the parent (rider) was placed. Demographic controls include placement age, gender, race, and nativity. Standard errors clustered by placement group in parentheses. A one-standard deviation change in household effects are larger than place effects across all outcomes. For first generation: household effects are approximately 5 times larger for income, 1.5 times larger for fertility, and 3.7 times larger for farming. For second generation: household effects are 4.4 times larger for income, 1.1 times larger for fertility, and 2.4 times larger for farming. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Migration by Placement Opportunity

	(1) Stayed in County	(2) Number of Moves	(3) Age at First Move	(4) Destination Opp
Opportunity Index	0.022*	-0.046*	0.045	0.044
	(0.011)	(0.024)	(0.274)	(0.029)
Placement Age	0.002	0.026***	-0.340***	-0.002
	(0.002)	(0.005)	(0.074)	(0.007)
Female	0.008	-0.275***	-0.103	0.086
	(0.013)	(0.044)	(0.758)	(0.070)
White	0.029	-0.051	5.143**	-0.145
	(0.059)	(0.194)	(2.154)	(0.305)
Native Born	-0.015	0.222***	-6.942***	-0.770***
	(0.018)	(0.062)	(0.989)	(0.069)
Observations	3,484	3,484	2,133	2,237
Control Mean	0.226	1.149	30.739	2.564
Orphanage-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports effects of placement opportunity on migration patterns. Adult location measured at ages 25-54. Column (1) shows the effects on who remained in placement county. Column (2) shows effects on the number of moves. Column (3) the effects of the age at first move for movers. Column (4) looks at the opportunity level of the counties moved to. All regressions include orphanage-year fixed effects and demographic controls. Standard errors are clustered at the county level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Geographic Scope of Migration

	(1) Stayed in State	(2) Left County, Stayed State	(3) Returned to NY	(4) Returned to NYC
Opportunity Index	-0.009	-0.030***	0.001	-0.002
	(0.007)	(0.010)	(0.002)	(0.002)
Placement Age	0.002	-0.000	-0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Female	0.077***	0.067***	-0.011***	-0.003
	(0.013)	(0.016)	(0.004)	(0.004)
White	-0.004	-0.011	-0.046	-0.049
	(0.062)	(0.069)	(0.043)	(0.038)
Native Born	0.001	0.021	-0.000	-0.002
	(0.016)	(0.021)	(0.005)	(0.005)
Observations	3484	3484	3008	3483
Control Mean	0.822	0.603	0.012	0.011
Orphanage-Year FE	Yes	Yes	Yes	Yes

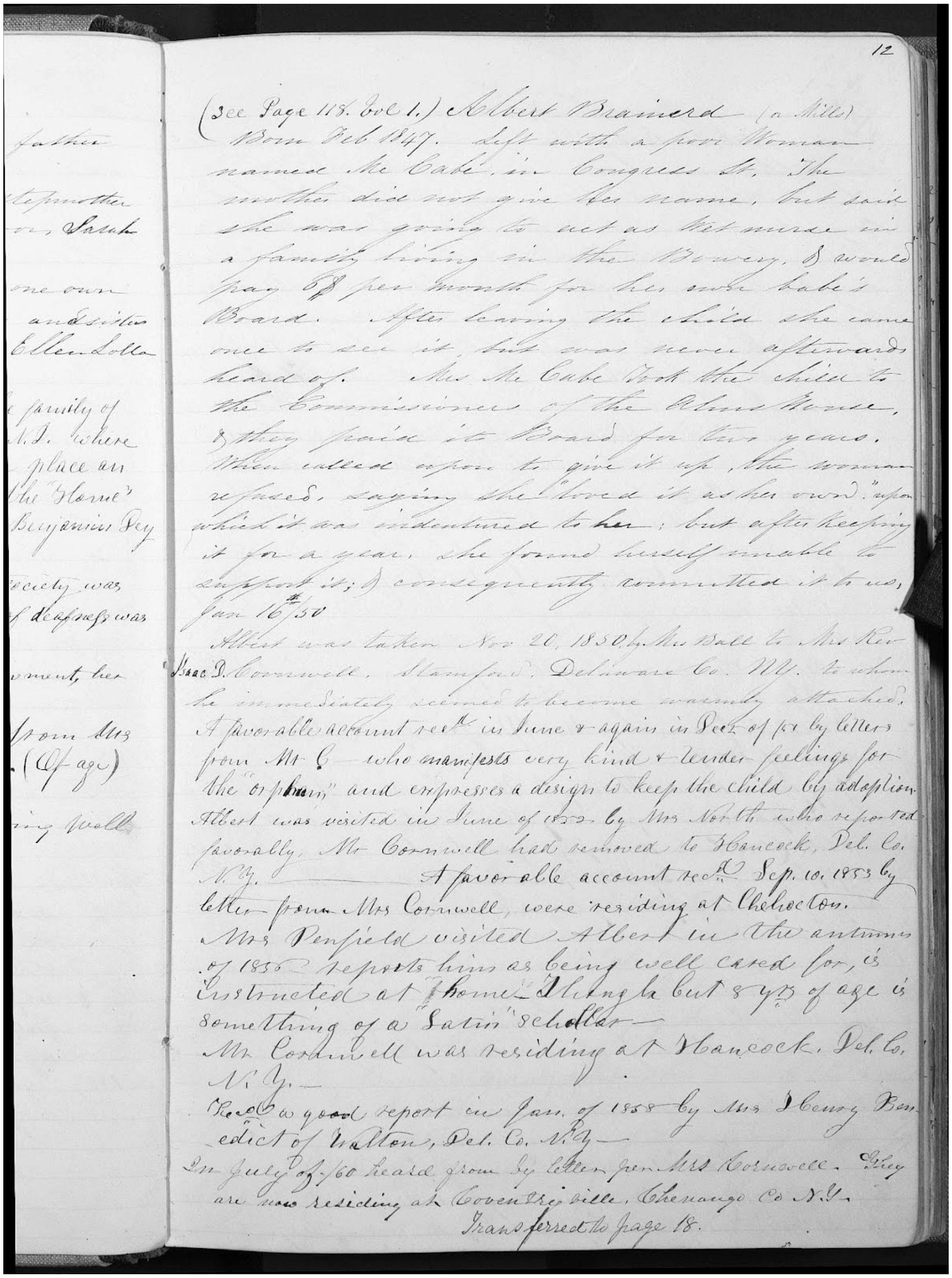
Notes: This table reports effects of placement opportunity on geographic patterns of migration. Adult location measured at ages 25-54. Columns (1) and (2) show effects for all riders. Columns (3) and (4) restrict the sample to riders placed outside New York. All regressions include orphanage-year fixed effects and demographic controls. Standard errors are clustered at the county level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

APPENDICES INTENDED FOR ONLINE PUBLICATION

A Additional Figures and Tables

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

Notes: This image shows an example of the selection process of riders. Orphaned children, in well dressed outfits of various ages, would be sent to the destination county and lined up at the arrival station's platform. Families interested in participating would speak with the children and orphanage agent and make a selection. Source: Making a Difference Project.



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(See Page 118. Vol 1.) Albert Brainerd (a Mills)

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 $8 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 Commissioner of the Alms House, & they paid its 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. NY. to whom he immediately seemed to become warmly attached. A favorable account rec'd in June & again in Dec. of '51 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 1856 reports him as being well cared for, is instructed at "home" though but 8 yrs of age is something of a "Latin" scholar—

Mr Cornwell was residing at Hancock. Del. Co. N.Y.—

Rec'd a good report in Jan. of 1858 by Mrs Henry Benedict of Walton, Del. Co. N.Y.—

In July of /60 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

Notes: Example of the ledgers digitized used from the American Female Guardian Society. Individuals were identified as riders based on the content of the document. Name, gender, age, placement family name, and placement date were extracted to identify individuals in the census. Source: AFGS ledger.

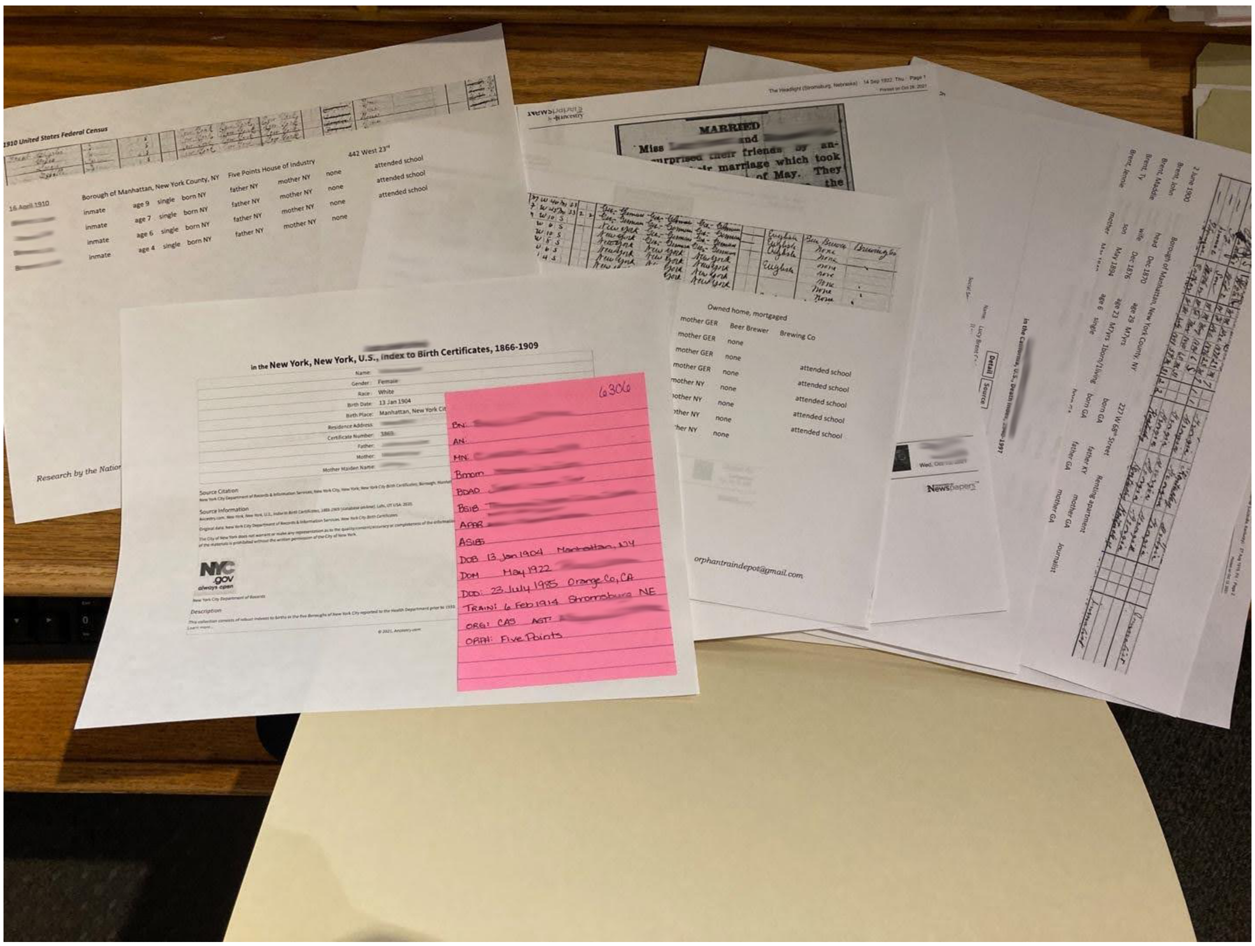

Figure A.3: Example of National Orphan Train Complex Research Document

Notes: Example of the files digitized used for the National Orphan Train Complex sample of riders. Information on Name, gender, age, placement family name, and placement date were extracted to identify individuals in the census. This image is altered to blur names.

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

Figure A.4: New York Juvenile Asylum Research Document

Notes: Example of the files digitized used for the New York Juvenile Asylum sample of riders. Name, gender, age, placement family name, and placement date were extracted to identify individuals in the census. Source: Kidder, Clark (2021) "A History of the New York Juvenile Asylum and Its Orphan Trains: Volume 2" pg. 16.

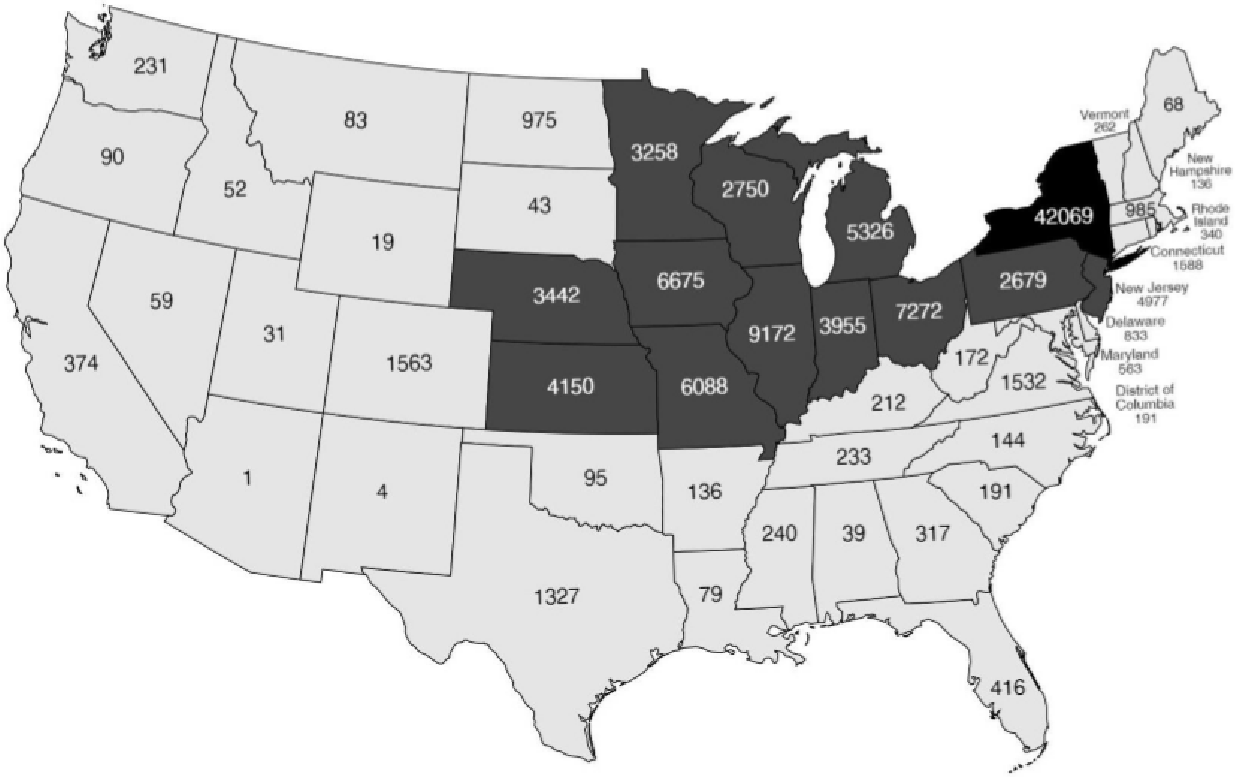

Figure A.5: Estimated Number of Child Placements Per State by the Children's Aid Society
Notes: Figure shows the estimated total geospatial distribution of rider destination locations across the United States by the largest participating orphanage the Children's Aid Society. Source: National Orphan Train Complex and Children's Aid Society annual reports

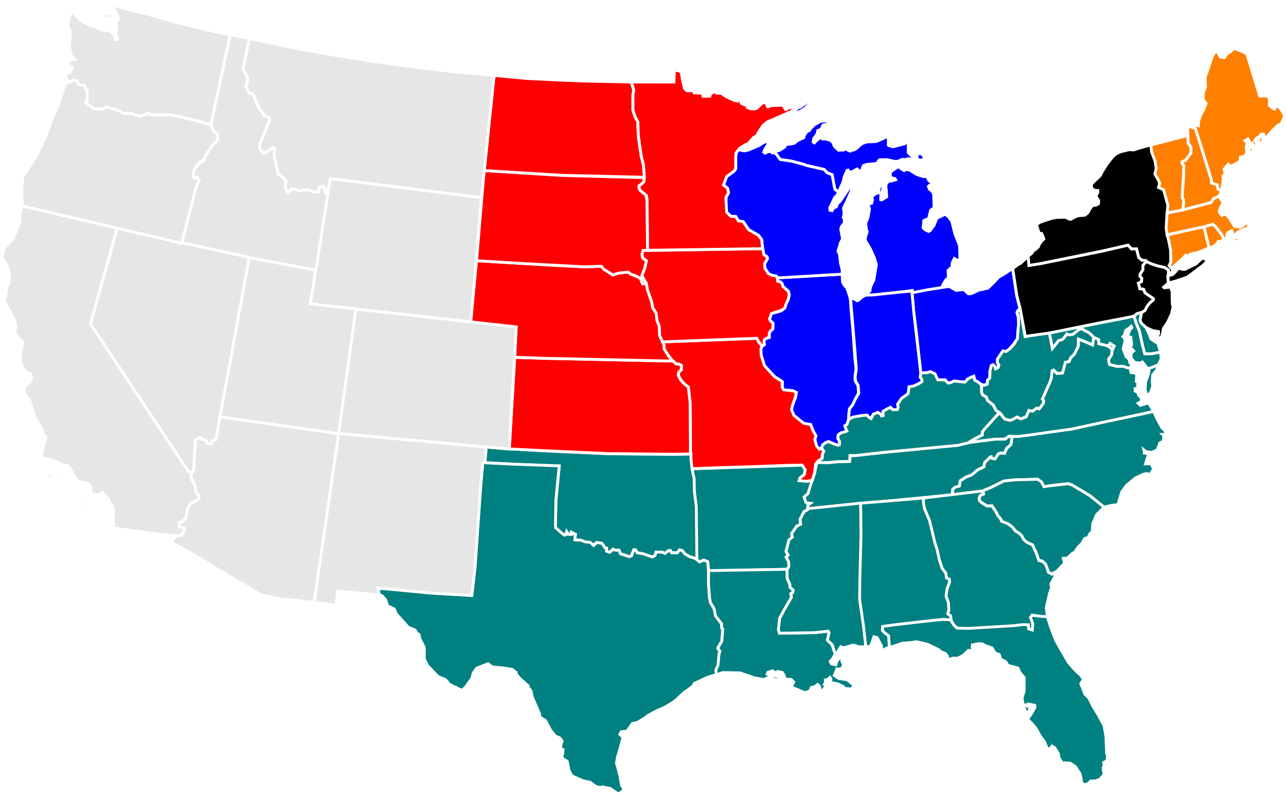

Figure A.6: Visualization of Geography Treatments

Notes: This figure displays the geospatial classification of place. Classifications made based on U.S. Census categorization. Black = Mid-Atlantic (baseline), Orange = New England, Teal = South, Blue = West Midwest, Red = East Midwest, Grey = West.

Table A.1: Summary Statistics by Census Year — NOTC Data

	1850	1860	1870	1880	1900	1910	1920	1930
Placement 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)
Observations	13	21	33	261	191	184	94	10

Notes: This table reports means and standard deviations, in parentheses, of four baseline characteristics (age, gender, race, native-born status) for orphans whose records were obtained through the National Orphan Train Complex (NOTC). As most NOTC records are created as a result of genealogical research by a descendant of an Orphan Train rider, we treat these riders as being from a separate orphanage group to account for systematic differences between riders in the NOTC data and other riders.

Table A.2: Summary Statistics by Census Year — NYJA Data

	1850	1860	1870	1880	1900	1910	1920	1930
Placement 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)	-
Observations	20	646	636	1413	620	-	2	-

Notes: This table reports means and standard deviations (listed below the mean) of four baseline characteristics (age, gender, race, native-born status) for orphans whose records were obtained through the New York Juvenile Asylum (NYJA). See Kidder (2003) for a detailed explanation of the data collection process. The years 1910 and 1930 had no reported riders from NYJA.

Table A.3: Summary Statistics by Census Year — AFGS and CAS Data

	AFGS		CAS	
	1880	1920	1880	1920
Placement 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)
Observations	817	33	748	169

Notes: This table reports means and standard deviations (listed below the mean) of four baseline characteristics (age, gender, race, native-born status) for orphans whose records were obtained through the American Female Guardian Society (AFGS) and Children's Aid Society (CAS). The AFGS ledgers are kept by the National Orphan Train Complex, but are separate data from the NOTC data referenced in Table A.1. See Inskeep (1996) for a detailed explanation of the data collection process for the CAS data.

Table A.4: Balance of Baseline Characteristics by Individual Treatment

	Above median	Below median	Difference
A. Literacy			
Female	0.262	0.255	0.007
			(0.016)
White	0.991	0.986	0.005
			(0.004)
Placement Age	12.433	12.996	-0.563***
			(0.155)
Native	0.856	0.833	0.023*
			(0.013)
B. Residential Development			
Female	0.264	0.254	0.01
			(0.016)
White	0.992	0.986	0.006
			(0.004)
Placement Age	12.62	12.772	-0.152
			(0.158)
Native	0.851	0.841	0.01
			(0.013)
C. Land Value			
Female	0.269	0.251	0.017
			(0.016)
White	0.993	0.985	0.008*
			(0.004)
Placement Age	12.487	12.850	-0.363**
			(0.16)
Native	0.876	0.826	0.05***
			(0.014)
D. Population			
Female	0.25	0.262	-0.012
			(0.017)
White	0.99	0.987	0.003
			(0.004)
Placement Age	12.803	12.663	0.139
			(0.164)
Native	0.848	0.843	0.005
			(0.014)

Notes: Table reports means for riders placed in above (below) median counties for each of the four characteristic definitions described in Section 4.1. Column 3 reports the difference in means, as well as the standard error of the associated t-test in parentheses and the corresponding p-value in brackets. Above (below) median status is determined at the county-census year level, and a county was considered above (below) median if the county average for each characteristic was higher (lower) than the median value of all placement counties in a given census year. Panel A reports differences based on county literacy rates. Panel B reports differences based on the fraction of individuals in a county living in a Census-designated place with population $\geq$ 2,500. Panel C reports differences based on average land values. Panel D reports differences based on total population.

Table A.5: Regression Balance Tests for Individual Treatments

	Literacy		Urbanicity		Land Value		Population	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.008	-0.020	0.024	0.024	0.018	0.038**	-0.006	0.013
	(0.021)	(0.019)	(0.021)	(0.018)	(0.021)	(0.015)	(0.021)	(0.017)
White	0.148*	0.051	0.140*	0.079	0.206***	0.115**	0.065	-0.018
	(0.083)	(0.071)	(0.077)	(0.070)	(0.071)	(0.058)	(0.078)	(0.059)
Placement Age	-0.008***	0.002	0.003	-0.000	0.002	0.004**	0.011***	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.022)
Native	0.059*	0.030	0.030	-0.069***	0.093***	-0.027	0.029	-0.058***
	(0.035)	(0.024)	(0.035)	(0.024)	(0.034)	(0.026)	(0.034)	(0.022)
F-Stat	4.70	1.25	1.92	3.00	4.32	3.81	6.58	2.03
P-Value	[0.001]	[0.289]	[0.106]	[0.018]	[0.002]	[0.004]	[0.000]	[0.088]
Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table reports regression balance tests for individual treatment measures. Dependent variables are the four county-level treatments (literacy, urbanicity, land value, population). Columns (1) and (2) show the results of regressing rider characteristics on literacy. Columns (3) and (4) show the results of regressing rider characteristics on urbanicity. Columns (5) and (6) show the results of regressing rider characteristics on land value. Columns (7) and (8) show the results of regressing rider characteristics on population. Odd numbered regressions do not include orphanage-by-placement-year fixed effects. Even numbered regressions include orphanage-by-placement-year fixed effects. Standard errors are clustered at the county-census year level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Normalized Differences Pairwise Treatment Comparisons

	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

Notes: This table contains the absolute value of the estimated normalized difference statistics for the covariate in each row and the individual treatment variable in each column. Each column compares the pair consisting of the treatment value between high and low-opportunity counties. 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 A.7: Regression Balance Test for Regional Treatments

	(1) East Midwest	(2) South	(3) West	(4) West Midwest
Female	-0.013	-0.001	-0.002	-0.004
	(0.010)	(0.005)	(0.002)	(0.007)
White	0.110**	-0.207***	0.006	0.065*
	(0.045)	(0.055)	(0.004)	(0.037)
Placement Age	0.003***	-0.001*	-0.000	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Native	-0.012	0.009***	-0.005	-0.001
	(0.016)	(0.003)	(0.003)	(0.008)
F-Stat	3.67	5.24	2.19	1.16
P-Value	(0.006)	(0.000)	(0.068)	(0.328)

Notes: This table reports regression balance tests across Census regions. Dependent variable is an indicator for each region. Each column represents a different region. The omitted category is Mid-Atlantic where New York City is located. New England is excluded due to insufficient observations. Each regression includes baseline characteristics (gender, age, race, native-born status) as independent variables and orphanage-by-placement-year fixed effects. Standard errors are clustered at the county-census year level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Normalized Differences Pairwise Region Comparisons

	East Midwest	New England	South	West	West Midwest
	(1)	(2)	(3)	(4)	(5)
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

Notes: 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 compares the region pair consisting of the Mid-Atlantic Census region (where New York City is located) and the Census region listed in the column. 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 A.9: Avg. Occ. Income Score with Household Characteristics by Treatment Type

	Average Occupational Income Score				
	(1)	(2)	(3)	(4)	(5)
Literacy	0.240				
	(1.036)				
Urbanicity		1.988**			
		(0.954)			
Land Value			1.799		
			(1.112)		
Population				2.092*	
				(1.114)	
Opportunity Index					1.073**
					(0.462)
HH Occ Score	0.296***	0.293***	0.294***	0.293***	0.293***
	(0.050)	(0.050)	(0.049)	(0.049)	(0.049)
Observations	2547	2547	2547	2547	2547
Low-Opp Mean	47.751	46.264	46.342	45.412	45.092
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Literacy	-1.073				
	(1.170)				
Urbanicity		1.850			
		(1.178)			
Land Value			2.612*		
			(1.374)		
Population				1.653	
				(1.235)	
Opportunity Index					0.921*
					(0.521)
Household Occ. Score	0.403***	0.397***	0.398***	0.399***	0.396***
	(0.040)	(0.040)	(0.039)	(0.040)	(0.040)
Observations	2,732	2,732	2,732	2,732	2,732
Low-Opp Mean	46.361	44.463	44.079	43.599	42.606
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of place on average occupational income score controlling for household characteristics at nearest census to arrival. Household characteristics is defined as father's occupational income score. Each column shows results for different treatments: opportunity index and individual treatments (literacy, urbanicity, land value, population). All regressions include orphanage-year fixed effects and demographic controls. Standard errors are clustered at the county level and displayed in parentheses. A one-standard deviation change in household occupational score effects are 2.5-3.8 times larger than individual place components for first generation, and 3.9-6.0 times larger for second generation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Fertility with Household Characteristics by Individual Treatments

	Number of Children				
	(1)	(2)	(3)	(4)	(5)
Literacy	0.062				
	(0.112)				
Urbanicity		-0.214**			
		(0.107)			
Land Value			-0.047		
			(0.118)		
Population				-0.234*	
				(0.121)	
Opportunity Index					-0.077
					(0.049)
Household Occ. Score	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2,547	2,547	2,547	2,547	2,547
Low-Opp Mean	2.360	2.520	2.499	2.512	2.698
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Literacy	0.044				
	(0.078)				
Urbanicity		-0.190**			
		(0.075)			
Land Value			-0.273***		
			(0.085)		
Population				-0.152*	
				(0.079)	
Opportunity Index					-0.104***
					(0.034)
Household Occ. Score	-0.017***	-0.017***	-0.017***	-0.017***	-0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	2732	2732	2732	2732	2732
Low-Opp Mean	1.713	1.830	1.837	1.777	1.978
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of place on fertility controlling for household characteristics at nearest census to arrival. Household characteristics is defined as father's occupational income score. Each column shows results for different treatments: opportunity index and individual treatments (literacy, urbanicity, land value, population). All regressions include orphanage-year fixed effects and demographic controls. Standard errors are clustered at the county level and displayed in parentheses. A one-standard deviation change in household occupational score effects are 1.9-9.4 times larger than individual place components for first generation, and 1.5-9.1 times larger for second generation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Farming Occupation with Household Characteristics by Individual Treatments

	Ever Worked in Farming				
	(1)	(2)	(3)	(4)	(5)
Literacy	0.024				
	(0.023)				
Urbanicity		-0.108***			
		(0.023)			
Land Value			-0.077***		
			(0.028)		
Population				-0.087***	
				(0.025)	
Opportunity Index					-0.043***
					(0.010)
Household Occ. Score	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,547	2,547	2,547	2,547	2,547
Low-Opp Mean	0.459	0.535	0.519	0.530	0.548
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Literacy	0.033				
	(0.026)				
Urbanicity		-0.068***			
		(0.023)			
Land Value			-0.085***		
			(0.029)		
Population				-0.061**	
				(0.026)	
Opportunity Index					-0.033***
					(0.012)
Household Occ. Score	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,732	2,732	2,732	2,732	2,732
Low-Opp Mean	0.314	0.368	0.363	0.364	0.380
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effects of place on farming occupation controlling for household characteristics at nearest census to arrival. Household characteristics is defined as father's occupational income score. Each column shows results for different treatments: opportunity index and individual treatments (literacy, urbanicity, land value, population). All regressions include orphanage-year fixed effects and demographic controls. Standard errors are clustered at the county level and displayed in parentheses. A one-standard deviation change in household occupational score effects are 2.1-9.7 times larger than individual place components for first generation, and 3.3-8.4 times larger for second generation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Migration by Placement Opportunity — All Ages

	(1) Stayed in County	(2) Number of Moves	(3) Age at First Move	(4) Destination Opp
Opportunity Index	0.016	-0.046*	0.045	0.021
	(0.011)	(0.024)	(0.274)	(0.029)
Placement Age	-0.005***	0.026***	-0.340***	-0.013*
	(0.002)	(0.005)	(0.074)	(0.007)
Female	-0.004	-0.275***	-0.103	-0.006
	(0.013)	(0.044)	(0.758)	(0.065)
White	0.072	-0.051	5.143**	-0.439*
	(0.060)	(0.194)	(2.154)	(0.250)
Native Born	-0.009	0.222***	-6.942***	-0.859***
	(0.019)	(0.062)	(0.989)	(0.070)
Observations	3,484	3,484	2,133	2,190
Control Mean	0.261	1.149	30.739	2.501
Orphanage-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports effects of placement opportunity on migration patterns using all adults ages 18+. Adult location is measured for all adults rather than restricting to prime-age adults. Column (1) shows the effects on who remained in placement county. Column (2) shows effects on the number of moves. Column (3) the effects of the age at first move for movers. Column (4) looks at the opportunity level of the counties moved to. All regressions include orphanage-year fixed effects and demographic controls. Standard errors are clustered at the county level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Geographic Scope of Migration — All Ages

	(1) Stayed in State	(2) Left County, Stayed State	(3) Returned to NY	(4) Returned to NYC
Opportunity Index	0.001	-0.015	-0.000	-0.001
	(0.007)	(0.011)	(0.002)	(0.001)
Placement Age	-0.004**	0.001	0.000	0.000
	(0.002)	(0.002)	(0.000)	(0.001)
Female	0.054***	0.053***	-0.009**	0.000
	(0.013)	(0.016)	(0.004)	(0.003)
White	0.028	-0.019	-0.046	-0.050
	(0.063)	(0.060)	(0.044)	(0.039)
Native Born	-0.006	0.005	-0.000	-0.009**
	(0.019)	(0.023)	(0.006)	(0.005)
Observations	3484	3484	3008	3483
Control Mean	0.863	0.612	0.011	0.008
Orphanage-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports effects of placement opportunity on geographic patterns of migration using all adults ages 18+. Adult location is measured for all adults rather than restricting to prime-age adults. Columns (1)-(2) show effects for all riders. Columns (3)-(5) restrict the sample to riders placed outside New York. All regressions include orphanage-year fixed effects and demographic controls. Standard errors are clustered at the county level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Alternative Specification for Contamination Bias on Individual Treatments

Table B.1: Correlation Matrix of Individual Treatments

	Literacy	Urbanicity	Land Value	Population
Literacy	1.000			
Urbanicity	-0.002	1.000		
Land Value	0.155**	0.425**	1.000	
Population	-0.130**	0.492**	0.387**	1.000

Notes: Correlations calculated in the full sample of riders (N=3,484). All correlations significant at $p < 0.05$ are indicated by **.

Table B.2: Horse Race and Long-Regression Comparison: First Generation

	Occ. Income Score		Number of Children		Ever Farmer	
	(1)	(2)	(3)	(4)	(5)	(6)
Literature (Lit)	0.251	-0.908	-0.050	0.009	0.021	0.014
	(0.810)	(1.204)	(0.093)	(0.138)	(0.019)	(0.027)
Urbanicity (Urb)	1.776**	3.034	-0.089	-0.006	-0.077***	-0.044
	(0.866)	(2.024)	(0.089)	(0.203)	(0.021)	(0.042)
Land Value (LV)	0.752	-0.695	0.015	-0.362	-0.045*	-0.081
	(0.941)	(3.036)	(0.100)	(0.229)	(0.024)	(0.072)
Population (Pop)	1.397	-1.368	-0.221**	-0.215	-0.046**	0.004
	(0.976)	(1.763)	(0.099)	(0.165)	(0.022)	(0.036)
LitxUrb		-2.685		-0.246		0.050
		(2.573)		(0.282)		(0.057)
LitxLV		0.859		0.455*		0.050
		(3.398)		(0.276)		(0.081)
LitxPop		6.960*		0.162		-0.105
		(3.668)		(0.356)		(0.068)
UrbxLV		-4.023		0.422		-0.034
		(4.000)		(0.381)		(0.099)
UrbxPop		-1.560		0.286		-0.096
		(2.656)		(0.310)		(0.060)
LVxPop		-1.565		0.088		0.095
		(3.849)		(0.474)		(0.097)
LitxUrbxLV		3.303		-0.339		0.014
		(4.854)		(0.469)		(0.116)
LitxUrbxPop		-3.560		-0.637		0.068
		(4.642)		(0.533)		(0.114)
LitxLVxPop		-2.945		-0.263		0.072
		(5.799)		(0.617)		(0.123)
UrbxLVxPop		9.096*		-0.474		-0.013
		(4.875)		(0.604)		(0.126)
LitxUrbxLVxPop		1.573		0.811		-0.154
		(7.154)		(0.814)		(0.173)
Observations	3,484	3,484	3,484	3,484	3,484	3,484
Control Mean	40.224	40.224	2.825	2.825	.518	.518
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table compares the horse race specification (where all four treatments enter simultaneously) with long regressions that sequentially add interaction terms between treatments for first generation riders. Columns (1), (3), and (5) show horse race specification. Column (2), (4), and (6) shows the long regressions. Outcomes are occupational income score (columns 1-2), number of children (columns 3-4), and ever farmer indicator (columns 5-6). All regressions include demographic controls and orphanage-year fixed effects. Standard errors are clustered at the county-census year level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Horse Race and Long-Regression Comparison: Second Generation

	Occ. Income Score		Number of Children		Ever Farmer	
	(1)	(2)	(3)	(4)	(5)	(6)
Literature (Lit)	-0.774	-2.394	0.022	-0.019	0.022	0.024
	(1.159)	(1.637)	(0.070)	(0.124)	(0.027)	(0.049)
Urbanicity (Urb)	1.567	4.716**	-0.203***	-0.391**	-0.076***	-0.135***
	(1.222)	(2.234)	(0.069)	(0.153)	(0.025)	(0.048)
Land Value (LV)	2.839*	16.070**	-0.230***	-0.720	-0.079***	-0.068
	(1.594)	(7.222)	(0.087)	(0.507)	(0.029)	(0.182)
Population (Pop)	0.386	0.652	-0.034	-0.219	-0.008	0.023
	(1.315)	(2.401)	(0.079)	(0.142)	(0.026)	(0.060)
LitxUrb		-4.236		0.190		0.101
		(3.494)		(0.200)		(0.097)
LitxLV		-12.358		0.521		0.005
		(7.702)		(0.521)		(0.188)
LitxPop		5.199		0.170		-0.076
		(3.904)		(0.211)		(0.082)
UrbxLV		1.520		0.229		0.106
		(10.571)		(0.637)		(0.236)
UrbxPop		-5.661*		0.460**		0.053
		(3.321)		(0.220)		(0.083)
LVxPop		-11.019		0.683		-0.170
		(7.640)		(0.581)		(0.192)
LitxUrbxLV		3.170		-0.407		-0.188
		(10.786)		(0.676)		(0.255)
LitxUrbxPop		8.310		-0.513		-0.123
		(6.007)		(0.320)		(0.137)
LitxLVxPop		8.843		-0.785		0.133
		(8.640)		(0.601)		(0.200)
UrbxLVxPop		-1.887		-0.555		0.024
		(11.047)		(0.731)		(0.242)
LitxUrbxLVxPop		-7.434		0.853		0.190
		(12.031)		(0.793)		(0.273)
Observations	3,059	3,059	3,059	3,059	3,059	3,059
Control Mean	42.303	42.303	2.001	2.001	.4	.4
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table compares the horse race specification (where all four treatments enter simultaneously) with long regressions that sequentially add interaction terms between treatments for second generation descendants. Columns (1), (3), and (5) show horse race specification. Column (2), (4), and (6) shows the long regressions. Outcomes are occupational income score (columns 1-2), number of children (columns 3-4), and ever farmer indicator (columns 5-6). All regressions include demographic controls and orphanage-year fixed effects. Standard errors are clustered at the county-census year level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Analysis on Native Children

Table C.1: Regression for Joint Balance Tests - Native Riders by Individual Treatments

	Literacy		Urbanicity		Land Value		Population	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.008	-0.020	0.024	0.023	0.018	0.038**	-0.006	0.012
	(0.021)	(0.019)	(0.021)	(0.018)	(0.021)	(0.015)	(0.021)	(0.017)
White	0.141*	0.047	0.137*	0.089	0.195***	0.119**	0.062	-0.010
	(0.083)	(0.071)	(0.077)	(0.069)	(0.071)	(0.058)	(0.077)	(0.060)
Placement Age	-0.008***	0.002	0.003	-0.000	0.001	-0.000	0.011***	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
F-Stat	5.04	1.04	2.13	1.06	2.76	4.80	8.71	0.31
P-Value	[0.002]	[0.375]	[0.095]	[0.366]	[0.041]	[0.003]	[0.000]	[0.816]
Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table reports regression balance tests for individual treatment measures across Census regions. Dependent variable is an indicator for each region. Each column represents a different region. Columns (1) and (2) show literacy, columns (3) and (4) show urbanicity, columns (5) and (6) show land value, and columns (7) and (8) show population. Odd-numbered columns exclude orphanage-by-placement-year fixed effects while even-numbered columns include them. The omitted category for each treatment is the low-opportunity measure (low literacy, low urbanicity, low land value, low population). F-statistic and p-value test joint significance of all covariates. Standard errors are clustered at the county-census year level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.