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

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Abstract

Where children grow up shapes their economic outcomes, but identifying causal place effects is difficult because families choose where to live. To overcome this challenge, 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 to an orphanage. We digitize archival records and link riders to Census data to measure long-run outcomes. We define place opportunity using county-level characteristics capturing education, urbanization, wealth, and labor market size. Riders placed in high-opportunity counties 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 similar marginal gains from high-opportunity places despite younger children having higher adult baseline earnings. Decomposing place effects by geographic scale shows household factors are approximately five times larger than county-level measures, though both are independently significant. Intergenerational transmission operates through a persistent change to individuals rather than geographic persistence, as effects continue despite high migration from riders' original placement counties. We provide the first causal evidence that place effects transmit and amplify 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 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, we lack causal evidence on intergenerational transmission of place effects. While research shows parental circumstances shape children's outcomes (Corak, 2013) and geography affects intergenerational mobility (Chetty, Hendren, Kline, & Saez, 2014), we do not know whether childhood place causally affects the next generation. Fourth, and finally, a fundamental identification challenge persists: when families move together in studies like MTO, we cannot separate neighborhood effects from household-level mechanisms, yet understanding this decomposition is essential for understanding the channels for which place affects individuals.

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. Younger children (placed before age 13) achieve higher baseline earnings in adulthood than older children, consistent with the value of earlier program participation. When examining marginal gains from high-opportunity versus low-opportunity placements, we find similar effects across age groups: younger children gain 2.74 percentile points while older children gain 2.44 percentile points, with overlapping confidence intervals. This pattern is consistent with diminishing returns in place capital accumulation: younger children benefit more from earlier placement overall but experience similar marginal returns from destination quality as older children, as gains operate along a flatter portion of the income production function when baseline capital is higher.

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 benefits extend to the next generation with effects that persist or amplify in magnitude. Critically, we demonstrate this transmission operates through durable changes to individuals rather than geographic persistence, as 77% of riders leave placement counties by prime working years. Finally, we document important heterogeneity in place effects by age at placement: younger children have higher baseline earnings from placement itself, while older children show larger marginal gains from high-opportunity counties, suggesting that baseline place capital shapes the returns from environmental improvements in ways that complement existing evidence on exposure effects.[1]

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

[1] We use "place capital" to describe advantages acquired from geographic environments, including human capital, financial capital, social capital, cultural capital, and location-specific opportunities and networks.

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 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 et al. (2014) identify structural factors in high-mobility areas, such as lower residential segregation, reduced income inequality, stronger social capital, greater family stability, and better schools, as key drivers of upward mobility.

Despite these advances, three key gaps remain in understanding place effects. First, existing research focuses primarily on poverty rates as the defining neighborhood characteristic, yet places vary across multiple dimensions that may independently drive outcomes. Second, when families move together, we cannot credibly separate household-level from neighborhood-level mechanisms, a challenge Oreopoulos (2003) identifies to understanding place. Third, although suggestive evidence exists that place matters for intergenerational mobility patterns, we lack causal estimates of whether childhood place effects transmit to the next generation independent of geographic persistence.

We note the parallel work by Abrahams and Keniston (2025), who also examine the effects of adoption and place using the Orphan Train Movement.[2] Our work differs from and extends theirs in several ways. We examine effects over the life course and extend the analysis to the intergenerational transmission of place effects. We examine potential mechanisms utilizing theoretical predictions drawn directly from the modern place effects

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

literature (Chetty & Hendren, 2018a; Chetty et al., 2014; Chyn & Katz, 2021). Additionally, our sample includes individuals from a different subset of orphanages and extends through the later period 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 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.[3] 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.

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[4], children are selected to board the next train to Town A using a "first in, first out mechanism"[5], 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

[3]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.

[4]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).

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

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)[6] 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 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

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

in the movement.

3.1 Orphan Data

The exact number of Orphan Train riders is not known.[7] While organizations in other large eastern United States cities participated in the movement, most of the children were placed by organizations in New York City. We focus on these institutions since they transported the largest number of children over the longest time period. According to the National Orphan Train Complex, the four largest participating orphanages in New York City were the Children's Aid Society (CAS), the New York Foundling Hospital (NYFH), the New York Juvenile Asylum (NYJA), and the American Female Guardian Society (AFGS). We collect data from three of the four prominent orphanages in New York City that participated in the Orphan Train Movement and used placement methods compatible with our identification strategy: CAS, NYJA, and AFGS.[8]

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

[7] 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.

[8] 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.

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.[9] 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.[10] Results are shown in Table 1. 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.[11] This matching process results in about 60% of the orphans in our data being linked to the U.S. Census.[12] 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.[13] 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

[9]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

[10]The specific Stata command used is reclink.

[11]This matching method is closest to the process used in Abramitzky, Boustan, and Eriksson (2014).

[12]See Price et al. (2021) for a discussion of linkage rates.

[13]See the Census Tree Project website for more information.

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[14] 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 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).[15] 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

[14]In our analysis, we drop individuals who are orphans but are determined to be non-riders

[15]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.

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.[16] 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 identification, or 3.5% of total riders[17].

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

[16]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.

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

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,[18] 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. Table 3 displays the summary stats of our four county characteristics.

Similar to Chyn and Shenhav (2025), we define treatment in our context as an indicator for being placed in a county that is above-median on each of these.[19] 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:

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

and $D_{k,ic}$ is an indicator equal to one if county c is above the median for characteristic k (literacy, urbanicity, land value, or population), 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'

[18]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).

[19]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.

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. $\mathbf{1}\{Count_{ic} = j\}$ are indicator variables equal to one if county c has exactly j above-median characteristics, and zero otherwise.

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.[20] 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 whether a particular treatment is driving the results, we estimate 4 which includes all four treatments simulta-

[20] We use binary indicators rather than continuous measures for simplicity and to allow for nonlinear effects. Appendix Table B.3 validates this approach using factor analysis and principal components analysis, confirming that a combined measure yield consistent results.

neously, allowing us to assess whether particular dimensions dominate.[21] 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 years old.[22;23] 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.

A challenge of our setting is defining "opportunity" or "better places" in the absence of standard modern measures like income or poverty rates. Following the development economics literature's approach to measuring multidimensional well-being through composite indices such as the Multidimensional Poverty Index (MPI) and Human Development Index (HDI), we construct an opportunity index from four county-level characteristics available in historical census data: literacy rates, urbanicity, land values, and population.

Our approach follows Chetty and Hendren (2018b), who emphasize that no single mea-

[21]Recent work by Goldsmith-Pinkham, Hull, and Kolesár (2024) has shown when multiple correlated treatments have heterogeneous effects, linear regressions may not fully capture the underlying treatment effect structure. Appendix C explores fully interacted specifications to assess treatment effect heterogeneity across different combinations of county characteristics. We interpret equation 3 as our primary estimates and use equation 4 as suggestive evidence for which of our dimensions matter the most.

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

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

sure fully captures neighborhood quality. Like the MPI, which aggregates across health, education, and living standards dimensions, our index captures complementary aspects of economic opportunity: human capital (literacy), economic development (urbanicity and land values), and labor market access (population). We define high-opportunity counties as those exceeding the median on at least three of four characteristics, allowing places to rank highly even with weakness in one dimension.

This threshold approach allows opportunity to vary across contexts while maintaining a comparable structure. A county with high literacy and urban amenities represents one form of opportunity, while a rural county with valuable land and growing population represents another, both providing economic mobility through different mechanisms. The summation approach captures this heterogeneity by permitting substitutability across dimensions: places can compensate for weakness in one characteristic (e.g., low literacy) with strength in others (e.g., high land values), reflecting the reality that multiple pathways to opportunity existed in the historical setting. We acknowledge significant researcher degrees of freedom in making this specification. To accommodate this, we validate this specification through factor analysis and principal components analysis (Appendix B), which confirm that these four characteristics load onto a common underlying factor, and through robustness checks using continuous measures (Appendix C), which yield substantively identical results.

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."[24] 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."[25]

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 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 4 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 5 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

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

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

with non-native riders as the differences are economically small and only marginally significant. Appendix D 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.[26] 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.

[26] 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.

5.1 Combined Effects of Place

We begin by examining the combined effects of place using our opportunity index approach. Table 6 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 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). Results are robust to using continuous standardized measures of all characteristics. Appendix Table B.3 validates the binary treatment using factor analysis and PCA.

5.2 Individual Effects of Place

Table 7 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.[27] Panel A displays results for first generation riders, and Panel B displays results for second generation riders.

[27] Results are robust to using continuous standardized measures of all characteristics (Appendix Tables C.4–C.6).

The estimates in Panel A indicate that when comparing riders in high and low-opportunity counties across the individual treatment definitions, 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 8 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 7. 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 9 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 neighborhood effects is an "exposure" effect: place effects on income are concentrated among younger children and increase in intensity with longer duration in better neighborhoods. We extend these findings by examining how place effects interact with placement age in our setting.

In Appendix E, we develop a simple model of place capital formation that generates testable predictions about age heterogeneity. The model predicts that while younger riders accumulate more place capital overall from being placed earlier, they may experience smaller marginal gains from high-opportunity placements due to diminishing marginal returns. This occurs because younger riders already possess higher baseline place capital from earlier placement in the Orphan Train movement.

To test these predictions empirically, we follow Chetty et al. (2016) and estimate separate regressions for younger and older children:

$$Y_{ico} = \alpha + \tau_1 T_{ic} + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{5}$$

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); X_i' includes demographic controls; and γ_{po} represents orphanage-by-placement-year fixed effects. We estimate this specification separately for children placed at age 12 or younger (young) and those placed older than 12 (old), with τ_1 capturing the treatment effect for each age group.[28]

Table 10 presents results examining how place effects vary by placement age using a split-sample approach. Panel A shows effects for children placed at age 12 or younger, while Panel B shows effects for older children. The table displays results across three outcomes:

[28] Appendix Table A.12 presents an alternative specification using interaction terms.

occupational income score (columns 1 and 4), fertility (columns 2 and 5), and farming propensity (columns 3 and 6). All specifications include demographic controls and orphanage-by-placement-year fixed effects.

For income effects, we find positive income gains from high-opportunity placement for both younger children (2.74 percentile points) and older children (2.44 percentile points). Our findings indicates limited age heterogeneity in income effects. This suggests that place effects on income operate similarly across age groups, with both younger and older riders benefiting comparably from high-opportunity placements.For fertility, high-opportunity placement reduces the number of children significantly for older children (-0.27 children).

For farming, high-opportunity placements substantially reduce farming propensity for both age groups, with younger children experiencing larger reductions (-12.1 percentage points) compared to older children (-7.4 percentage points). Both effects are highly significant. This pattern is consistent with exposure effects, where younger children who spend more formative years in high-opportunity locations are more likely to pursue non-agricultural occupations in adulthood.

The similar income effects across age groups, illuminate an important distinction between place capital accumulation and income production. Our theoretical framework in Appendix E suggests that younger children may accumulate more place capital from high-opportunity counties due to longer exposure, consistent with Chetty et al. (2016), but experience these gains along a flatter portion of the concave function due to their higher baseline capital from earlier placement. Conversely, older children accumulate less place capital but experience larger marginal gains due to diminishing marginal returns. The offsetting of exposure effects and diminishing returns produces similar observed income effects even when underlying capital accumulation differs by age. This pattern suggests that measuring income effects alone may mask underlying place capital effects.

5.3.2 Gender Heterogeneity in Place Effects

We examine whether the effects of destination characteristics vary by gender. Following the approach in Chetty et al. (2016), we estimate separate regressions for male and female riders to allow all coefficients to vary by gender:

$$Y_{ico} = \alpha + \tau_1 T_{ic} + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{6}$$

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); X_i' includes demographic controls; and γ_{po} represents orphanage-by-placement-year fixed effects. We estimate this specification separately for male and female riders, with τ_1 capturing the treatment effect for each gender.[29]

Table 11 presents results examining how place effects vary by gender using a split-sample approach. Columns 1-3 present results for male riders, while columns 4-6 present results for female riders. The table displays results across three outcomes: occupational income score (columns 1 and 4), fertility (columns 2 and 5), and farming propensity (columns 3 and 6). All specifications include demographic controls and orphanage-by-placement-year fixed effects.

For occupational income scores, we find large gender differences in place effects. Male riders experience significant gains from high-opportunity placements (3.36 percentile points), while female riders show no detectable income effect. This substantial difference suggests that place-based advantages translated into occupational mobility for men but not for women. The lack of occupational returns for women likely reflects severe historical constraints on women's labor market opportunities in the early 20th century. Female riders' baseline occupational scores in low-opportunity counties average only 8.73 percentile points compared to 52.83 percentile points for male riders, reflecting the limited occupational pathways avail-

[29] Appendix Table A.13 presents an alternative specification using interaction terms.

able to women regardless of location. Geographic advantages did not improve gender-based occupational barriers that characterized the period.

In contrast to occupational outcomes, place effects on fertility and farming operate for both genders. High-opportunity placements reduce fertility for both male riders (0.20 fewer children) and female riders (0.44 fewer children), with female riders showing a somewhat larger response. The fertility effects suggest that high-opportunity counties—characterized by greater urbanization, higher land values, greater educational attainment, and higher labor force diversity fostered environments associated with smaller family sizes for both genders.

Similarly, high-opportunity placements reduce farming propensity for both male riders (9.1 percentage points) and female riders (10.5 percentage points). Both effects are highly significant and similar in magnitude. Female riders in low-opportunity counties show lower baseline farming rates (44.8%) compared to male riders (50.7%), but both genders respond similarly to county characteristics. These patterns suggest that while geographic characteristics shaped family formation decisions and agricultural participation for both genders, place-based advantages contributing to occupational income scores were largely restricted to men during this historical period.

5.3.3 Differences in Place Effects in Earlier and Later Years

We examine whether the effects of destination characteristics vary by placement period, splitting the sample at 1890. This division captures important institutional changes in child placement practices during the Orphan Train era. By 1890, state charity boards were being established to provide oversight of placement organizations. By 1899, thirty states had created such boards to supervise both public and private child placement agencies (Trammell, 2009). The period around 1890 also marked growing criticism of Orphan Train placement practices, with reviews conducted in the 1880s and 1890s recommending improved investigation and supervision of placements. While orphan trains continued operating until 1929, the increasing professionalization of social work and expanding government involvement in child welfare during the 1890s represented meaningful changes in the institutional environment. Our pre/post-1890 split captures whether these evolving practices affected the quality of placement matches and subsequent child outcomes.

We estimate separate regressions for riders placed before 1890 and those placed in 1890 or after:

$$Y_{ico} = \alpha + \tau_1 T_{ic} + X_i'\beta + \gamma_o + \epsilon_{ico} \tag{7}$$

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); X_i' includes demographic controls; and γ_o represents orphanage fixed effects. We estimate this specification separately for the early period (before 1890) and late period (1890 and after), with τ_1 capturing the treatment effect for each period. Placement year fixed effects are not included as time period is the dimension of heterogeneity being examined.[30]

Table 12 presents results examining how place effects vary across time periods using a split-sample approach. Columns 1-3 present results for riders placed before 1890 (the early period), while columns 4-6 present results for riders placed in 1890 or after (the late period). The table displays results across three outcomes: occupational income score (columns 1 and 4), fertility (columns 2 and 5), and farming propensity (columns 3 and 6). All specifications include demographic controls and orphanage fixed effects.

For occupational income scores, we find similar treatment effects across time periods. Early period riders experience significant gains from high-opportunity placements (3.00 percentile points), while late period riders show marginally significant comparable effects (3.32 percentile points). The similarity in point estimates (difference of 0.32 percentile points) indicates that place effects on occupational outcomes remained stable throughout the program's duration.

For fertility, high-opportunity placements reduce the number of children in both peri-

[30] Appendix Table A.14 presents an alternative specification using interaction terms.

ods, with early period riders experiencing similar reductions (0.31 fewer children) compared to late period riders (0.37 fewer children). Both effects are statistically significant. The similar magnitudes suggest that county characteristics shaped family formation decisions consistently throughout the program period.

For farming, high-opportunity placements substantially reduce farming propensity in both periods. Both early period riders and late period riders show significant reductions (10.6 percentage points vs 12.5 percentage points) in farming propensity. Additionally, The baseline farming rates are comparable across periods (49.1% in early period, 49.6% in late period), and both groups respond similarly to county characteristics.

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.[31]

Specifically, we define the empirical design as follows:

$$Y_{ico} = \alpha + \sum_{j=1}^{5} \eta_j L_{ij} + X_i' \beta + \gamma_{co} + \epsilon_{ico} \tag{8}$$

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

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

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 13, 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 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: decomposing place effects by geographic scale, 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 decomposing them into household-level and county-level components. 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. It is important to note that while county assignment is quasi-random the matching of specific children to specific households within counties involves selection. This means household effects are causally identified as part of the place treatment, but the relative magnitude of household versus county effects may be influenced by within-county sorting if better households systematically select children on latent factors that in part determine our set of outcomes.

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:

$$Y_{ico} = \alpha + \tau_1 OpportunityIndex_i + \tau_2 HouseholdOccScore_i + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{9}$$

where we include both the opportunity index and household occupation score simultaneously to decompose the total effect of placement into household-level and county-level place components. Table 14 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. Household income 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 (first generation) income, providing an estimate of intergenerational elasticity. Column 2 reveals an IGE of 0.175. Modern estimates of intergenerational elasticity in the United States range from 0.34 to 0.5 depending on data sources and methodology (Chetty et al., 2014; Corak, 2013; Solon, 1992), suggesting relatively high intergenerational mobility. The ratio of household-level to county-level place effects remains large at 4.4 times for income, though county-level effects continue to operate independently. [32]

We consider that on interpreting the effects household quality may be endogenous to child characteristics within counties. Therefore, our household estimates reflect both the genuine effect of household quality and potential positive selection. The five-to-one ratio of household to county effects should be interpreted as an upper bound, though the persistence of county effects even after controlling for household selection provides strong evidence that macro-level place characteristics matter independently.

[32] 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.

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, or if the transmission is occurring through parents shaping their children irrespective of their next location. To understand how these channels contribute to the observed outcomes of children of Orphan Train riders, consider the following stylized model:

$$Y_{child} = f(X_{parent,place}) + f(Z_{place}) \tag{10}$$

In this model, the observed outcomes of children are a combination of advantages transmitted from parent to child, in part shaped by their own placement location ($X_{parent,place}$), as well as place-specific advantages that are independent of parent characteristics (Z_{place}). The $X_{parent,place}$ term captures advantages that parents acquired in their placement environments and transmitted to children whether through active parenting, financial transfers, networks, or children's own experiences shaped by their parents' resources. The Z_{place} term captures location-specific advantages that children receive directly from residing in their current county, independent of parental transmission. This framework generates testable predictions about migration patterns. If intergenerational effects transmit primarily through continued geographic exposure, we should observe: (1) riders staying in high-opportunity placements, and (2) children remaining in their parents' placement counties. Conversely, if transmission operates through parental advantages, intergenerational effects should persist even when families migrate away from placement counties.

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

$$M_{ico} = \alpha + \delta_1 OpportunityIndex_i + X_i'\beta + \gamma_{po} + \epsilon_{ico} \tag{11}$$

where M_{ico} represents various migration outcomes. For Table 15, 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 16, outcomes are staying in placement state, leaving both county and state, and returning to New York.

Table 15 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).[33] 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 16 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

[33] Tables A.15 and A.16 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.

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 or New York City. 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 relatively modest place inertia among first-generation riders (2.2 percentage points increase in staying), geographic mobility remained high as approximately 77% of riders left their placement county by prime working years, and geographic persistence was even lower among second-generation children. The persistence and strengthening of place effects across generations, despite this high mobility, provides evidence that intergenerational transmission operates primarily through parent-based advantages rather than continued geographic exposure to the same high-opportunity environment. Children benefited from their parents' placement opportunity even when living in entirely different locations, consistent with parents transmitting advantages, opportunities, or other forms of resources acquired during their formative years in high-opportunity environments.

7 Discussion

Our analysis reveals three central findings about how place shapes economic outcomes across generations. First, we provide the first causal evidence that place effects transmit intergenerationally. Children of riders placed in high-opportunity counties have higher incomes and lower fertility, with effects that persist or amplify across generations. Second, household quality dominates place quality in determining outcomes, with effects approximately five times larger for income, yet county-level place effects persist independently even after controlling for household characteristics. Third, examining place dimensions separately shows that urbanization, land values, and population drive long-run effects. These findings advance in place effects literature regarding intergenerational transmission, the household-place decomposition, and which specific dimensions of opportunity matter most.

A central contribution is decomposing place effects into household and county components, addressing a fundamental challenge in the place effects literature. When families move together, we cannot separate neighborhood from household mechanisms. The Orphan Train setting allows us to observe both channels. We interpret household quality as a micro-level component of place: quasi-random county assignment determines the pool of available families, making household exposure a causal place effect. However, within-county matching between families and children involves selection, so the relative magnitudes of household versus county effects should be interpreted cautiously. With this framework, we find household effects approximately five times larger than county effects for income, yet county-level effects remain statistically significant independently. Both channels strengthen intergenerationally, with household associations increasing from 0.147 to 0.175 and place effects from 0.815 to 1.108, suggesting genuine transmission of advantages acquired through both household and county environments.

A critical question is whether intergenerational effects operate through geographic persistence or through changes to individuals. We find strong evidence for the latter mechanism. Approximately 77% of first-generation riders migrate away from their placement counties by prime working years, yet place effects persist and amplify in the second generation. High-opportunity placement increases the probability of remaining in the placement county by only 2.2 percentage points, an effect that cannot account for the observed intergenerational transmission. Second-generation children are even less likely to reside in their parents' original placement counties. Despite this high geographic mobility, place effects strengthen across generations, with opportunity index coefficients increasing from 0.815 to 1.108 for income. This pattern demonstrates that place effects transmit through persistent changes to individuals rather than through continued exposure to the same geographic environment.

Our estimated intergenerational elasticity of 0.175 reveals high income mobility compared to both historical and modern estimates. Historical IGE estimates for biological children in this era range from 0.40 to 0.60 (Buckles et al., 2023), while modern estimates range from 0.34 to 0.50. The substantially lower IGE among orphan train riders likely reflects the family dynamics among placed children. Historical accounts indicate the relationship between riders and families varied significantly, ranging from informal adoption to indentured servitude. It is likely that a significant portion of the children in this sample never received inheritance or financial support after their time in the household. This explains why our IGE estimate captures primarily human capital transmission rather than wealth transfers characteristic of biological families.[34]

Several heterogeneity patterns provide additional insight into how place effects operate. First, age heterogeneity reveals that younger children benefit more from the Orphan Train program itself, achieving higher baseline earnings in adulthood. However, the marginal gains from high-opportunity versus low-opportunity placements are similar across age groups, consistent with diminishing returns: younger children accumulate more place capital from earlier placement due to the "exposure effect" documented in the MTO literature but experience these gains along a flatter portion of the income production function. This pattern suggests baseline place capital shapes returns. Second, gender patterns reveal similar marginal gains from place for men and women despite an 82% baseline earnings gap, indicating place effects may operate through channels beyond direct labor market access. Third, place effects remain relatively stable across the Orphan Train Movement era despite substantial economic transformation from 1853-1929. Finally, regional heterogeneity shows particularly strong effects in agricultural regions including the South and West Midwest, though income effects vary more than fertility and farming effects across regions.

Our findings extend the modern place effects literature in several ways. While MTO demonstrated that moving to lower-poverty neighborhoods improves children's outcomes,

[34] Historical accounts suggest that children were to be given a small stipend and a pair of clothes on their 18^{th} birthday a value much less than typical inheritance of biological children.

we examine placements across substantially more diverse geographic contexts providing evidence that place effects operate beyond typical metropolitan settings. Additionally, we identify which specific dimensions of opportunity independently drive outcomes, demonstrating that urbanization, land values, and labor market size matter extending beyond a focus on poverty rates. We decompose place effects into household and county components, addressing a fundamental identification challenge where families typically move together. We find household quality dominates county characteristics but both operate independently, revealing that place effects occur at multiple scales. The age heterogeneity we document also differs from standard exposure effects: younger children benefit more but show similar marginal gains from high versus low opportunity destinations, consistent with diminishing returns in place capital accumulation. The historical setting reveals that place effects operate even without modern institutions suggesting fundamental economic structures drive these patterns.

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 specified treatment definitions. Finally, we hope that future work will seek to disentangle additional heterogeneity among subgroups of riders, particularly understanding the complex relationships among riders and their families, potential yielding additional insights that are obfuscated by high-level analysis.

Despite these limitations, our findings offer several insights for contemporary policy. First, the substantial dominance of household effects over county effects suggests that policies should prioritize household quality and family support. Second, among place dimensions, urbanization and labor market size emerge as the primary drivers of long-run effects, indicating that place-based policies should focus on labor market access and agglomeration.

Third, the independent persistence of county-level place effects even after controlling for household quality demonstrates that place-based interventions can generate returns beyond household-level mechanisms. Fourth, the intergenerational transmission and amplification of both household and place effects imply that early interventions generate social returns extending beyond the directly treated generation such that current policies targeting place-based programs may be undervaluing the benefits of it's investment.

8 Conclusion

We provide causal evidence on how place shapes long-run and intergenerational socioeconomic outcomes by examining the Orphan Train Movement, which relocated hundreds of thousands of displaced children from New York City to families throughout the United States between 1853 and 1929. Leveraging quasi-random placement based on institutional features, we find that children placed in high-opportunity counties experience higher lifetime earnings, lower fertility, and are less likely to work in agriculture with effects that persist and amplify across generations. Examining place dimensions separately reveals that urbanization, land values, and labor market size drive these effects, while literacy shows no independent impact.

Our analysis makes several contributions to the place effects literature. We provide the first causal evidence that place effects transmit intergenerationally through durable changes to individuals rather than geographic persistence, as effects strengthen despite a significant portion of riders leaving their placement counties. We decompose place effects into household and county components, revealing that household quality dominates but both channels operate independently and amplify across generations. Finally, we demonstrate which specific dimensions of opportunity matter, extending beyond the poverty-focused measures in contemporary studies.

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Tables and Figures

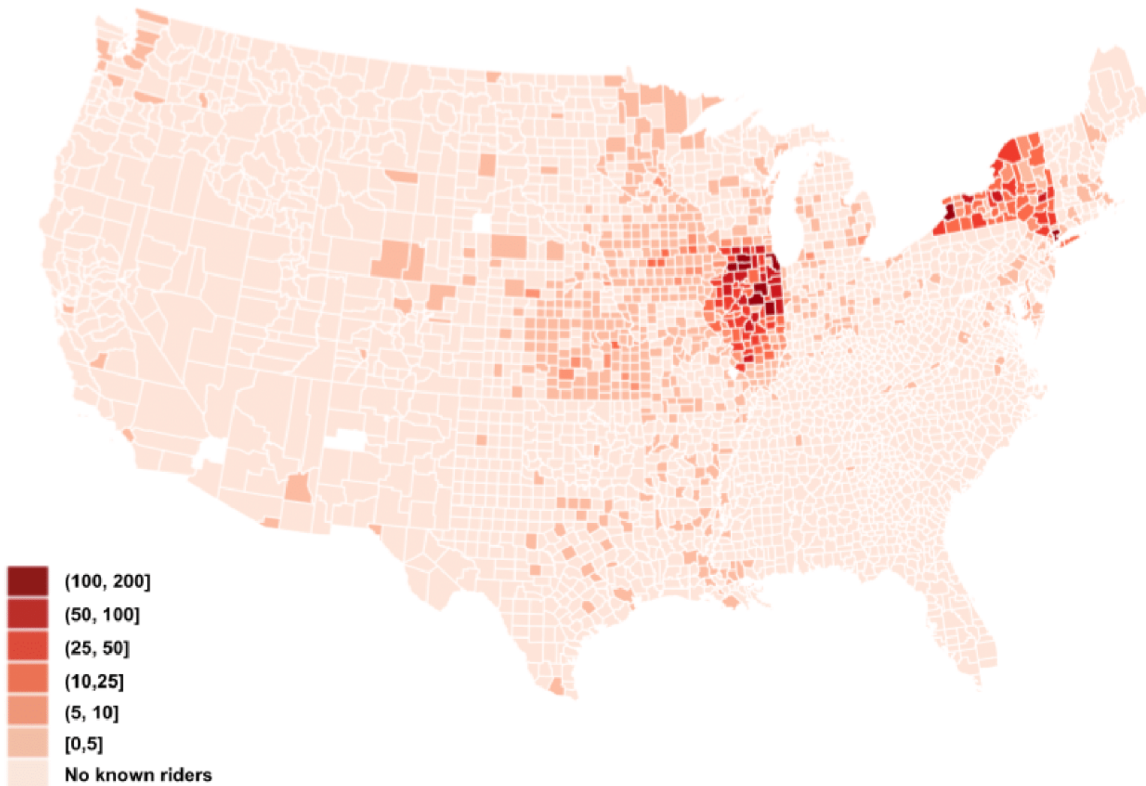

Figure 1: Distribution of Riders by Destination County

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.

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: Summary Statistics: County Treatment Variables

	Mean	Median	SD	Min	Max	N
Panel A: First Generation						
Literacy	0.942	0.952	0.052	0.405	0.999	3,481
Urbanicity	0.208	0.159	0.237	0.000	1.000	3,481
Land Value	46.878	37.000	119.348	2.000	6,032	3,462
Population	59,827	28,3250	147,133	55	3,022,513	3,481
Panel A: Second Generation						
Literacy	0.938	0.949	0.057	0.537	0.999	4,554
Urbanicity	0.161	0.114	0.190	0.000	1.000	4,554
Land Value	40.709	33.000	142.063	2.000	6,032	4,539
Population	36,427	27,580	42,481	66	813,154.	4,554

Notes: This table reports summary statistics for the four county-level treatment variables used in the analysis. Panel A shows statistics for Generation 1 (Orphan Train riders). Panel B shows statistics for Generation 2 (children of riders). Literacy measures the proportion of the county population that is literate. Urbanicity measures the proportion of county residents living in urban areas. Land value is the average value of land per acre in the county. Population is the total county population. All variables are measured at the time of rider placement using data from the U.S. Census.

Table 4: 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 5: 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 6: 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 7: 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: This table follows a similar structure to Chyn, Collinson, and Sandler (2025) Table V. 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. Note as the treatment variable for each column changes the control groups for each regression differs. 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 8: 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: This table follows a similar structure to Chyn et al. (2025) Table V. 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. Note as the treatment variable for each column changes the control groups for each regression differs. 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 9: 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: This table follows a similar structure to Chyn et al. (2025) Table V. 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. Note as the treatment variable for each column changes the control groups for each regression differs. 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 10: Age Heterogeneity in Place Effects: Split Sample Specification

	Panel A: Young Children			*Panel B: Older Children*		
	Income	Fertility	Farming	Income	Fertility	Farming
	(1)	(2)	(3)	(4)	(5)	(6)
High treatment	2.745*	-0.191	-0.121***	2.441**	-0.274**	-0.074***
	(1.474)	(0.130)	(0.034)	(1.197)	(0.133)	(0.028)
Observations	1,581	1,581	1,581	1,882	1,882	1,882
Control Mean	40.818	2.604	0.480	42.407	2.686	0.502
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table shows split regression based on placement age following Chetty and Hendren (2018a) Table 3. Each column reports coefficients from separate regressions examining place effects by placement age. Panel A restricts the sample to children placed at age 12 or younger. Panel B restricts the sample to children placed older than age 12. Columns (1) and (4) show effects on average occupational income score. Columns (2) and (5) show effects on fertility (total number of children). Columns (3) and (6) show effects on ever farming in adulthood. High opportunity is defined as being placed in a county with 3 or 4 above-median characteristics on the opportunity index. Control mean refers to riders in low-opportunity counties (0-2 characteristics) within each age group. All specifications include demographic controls (gender, race, and immigrant status) and orphanage-by-placement-year fixed effects. Standard errors are clustered at the placement county level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Gender Heterogeneity in Place Effects: Split Sample Specification

	Panel A: Men			*Panel B: Women*		
	Income	Fertility	Farming	Income	Fertility	Farming
	(1)	(2)	(3)	(4)	(5)	(6)
High Treatment	3.359***	-0.203**	-0.091***	0.699	-0.445**	-0.105**
	(1.113)	(0.102)	(0.027)	(1.304)	(0.202)	(0.043)
Observations	2,596	2,596	2,596	870	870	870
Control Mean	52.825	2.599	0.507	8.730	2.793	0.448
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table shows split regression based on placement age following Chetty and Hendren (2018a) Table 7. Each column reports coefficients from separate regressions examining place effects by gender. Columns 1-3 restrict the sample to male riders. Columns 4-6 restrict the sample to female riders. Columns (1) and (4) show effects on average occupational income score. Columns (2) and (5) show effects on fertility (total number of children). Columns (3) and (6) show effects on ever farming in adulthood. High opportunity is defined as being placed in a county with 3 or 4 above-median characteristics on the opportunity index. Control mean refers to riders in low-opportunity counties within each gender group. All specifications include demographic controls (age at placement, race, and immigrant status) and orphanage-by-placement-year fixed effects. Standard errors are clustered at the placement county level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Time Period Heterogeneity in Place Effects: Split Sample Specification

	Panel A: Early Period			*Panel B: Late Period*		
	Income	Fertility	Farming	Income	Fertility	Farming
	(1)	(2)	(3)	(4)	(5)	(6)
High Treatment	3.000***	-0.309***	-0.106***	3.322*	-0.372**	-0.125***
	(1.145)	(0.113)	(0.031)	(1.799)	(0.149)	(0.039)
Observations	2,764	2,764	2,764	731	731	731
Control Mean	41.788	2.697	0.491	40.812	2.279	0.496
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports coefficients from separate regressions examining place effects by time period. Columns 1-3 restrict the sample to riders placed before 1890. Columns 4-6 restrict the sample to riders placed in 1890 or after. Columns (1) and (4) show effects on average occupational income score. Columns (2) and (5) show effects on fertility (total number of children). Columns (3) and (6) show effects on ever farming in adulthood. High opportunity is defined as being placed in a county with 3 or 4 above-median characteristics on the opportunity index. Control mean refers to riders in low-opportunity counties within each time period. All specifications include demographic controls (age at placement, gender, race, and immigrant status) and orphanage fixed effects. Standard errors are clustered at the placement county level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Effect of Place by Geography

	Occ. Income Score (1)	Fertility (2)	Farming (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 14: 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 occupational 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 binary place-based treatment measuring whether the placement county exceeds the median on at least three of four characteristics (literacy, urbanicity, land value, population); one standard deviation equals 1.29 for Generation 1 and 1.17 for Generation 2. Household Occ. Score is the foster father's occupational income score percentile rank nearest to placement year for Generation 1, and the father's occupational income score percentile rank nearest to age the parent (rider) was placed for Generation 2; one standard deviation equals 34.97 for Generation 1 and 32.36 for Generation 2. All regressions include demographic controls (placement age for Gen 1, birth year for Gen 2, gender, race, and nativity) and orphanage-year fixed effects. Standard errors clustered at the county-census year level and displayed in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: 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 16: 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.

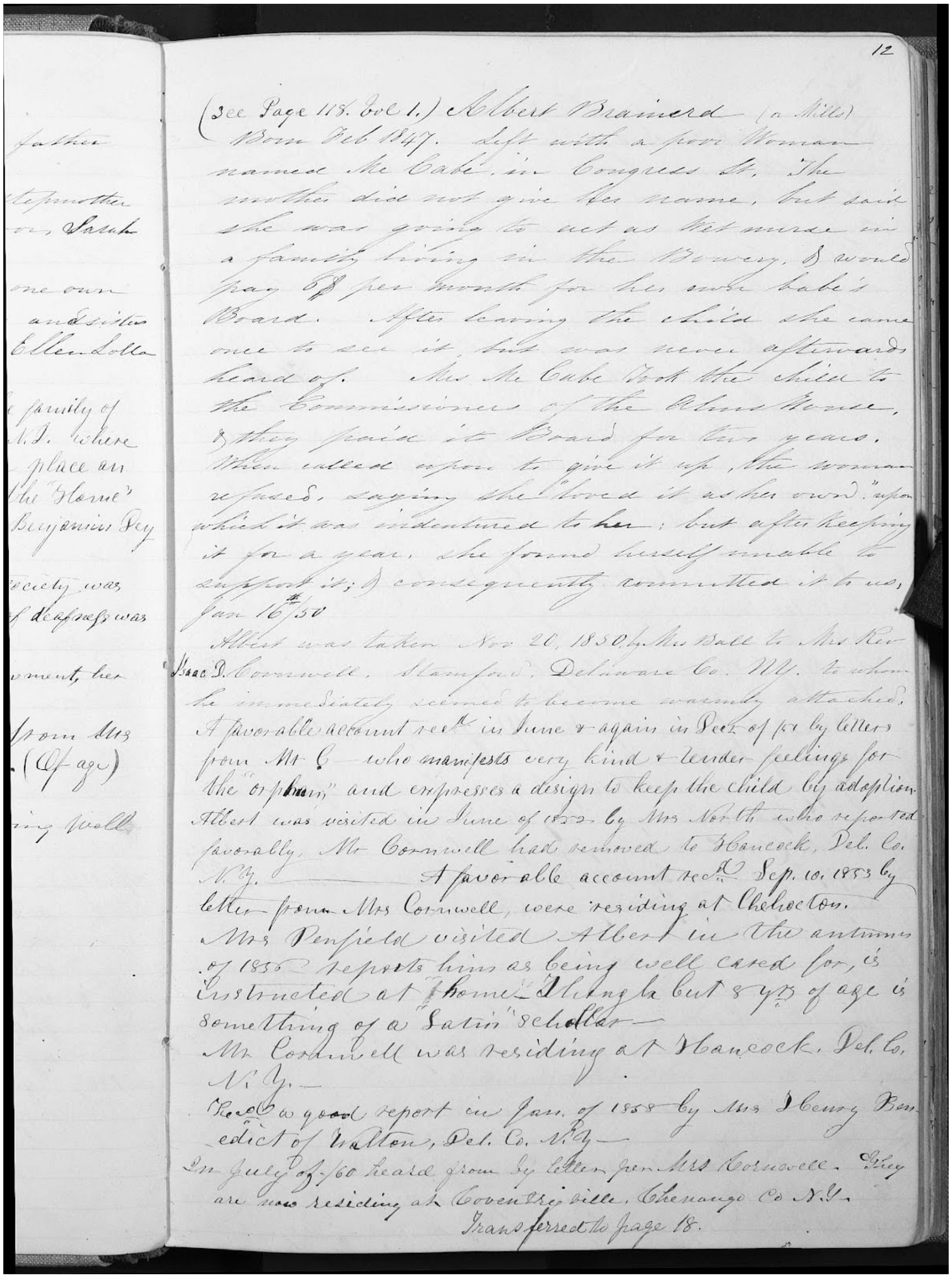

Figure A.2: Example of American Female Guardian Society Ledgers

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.

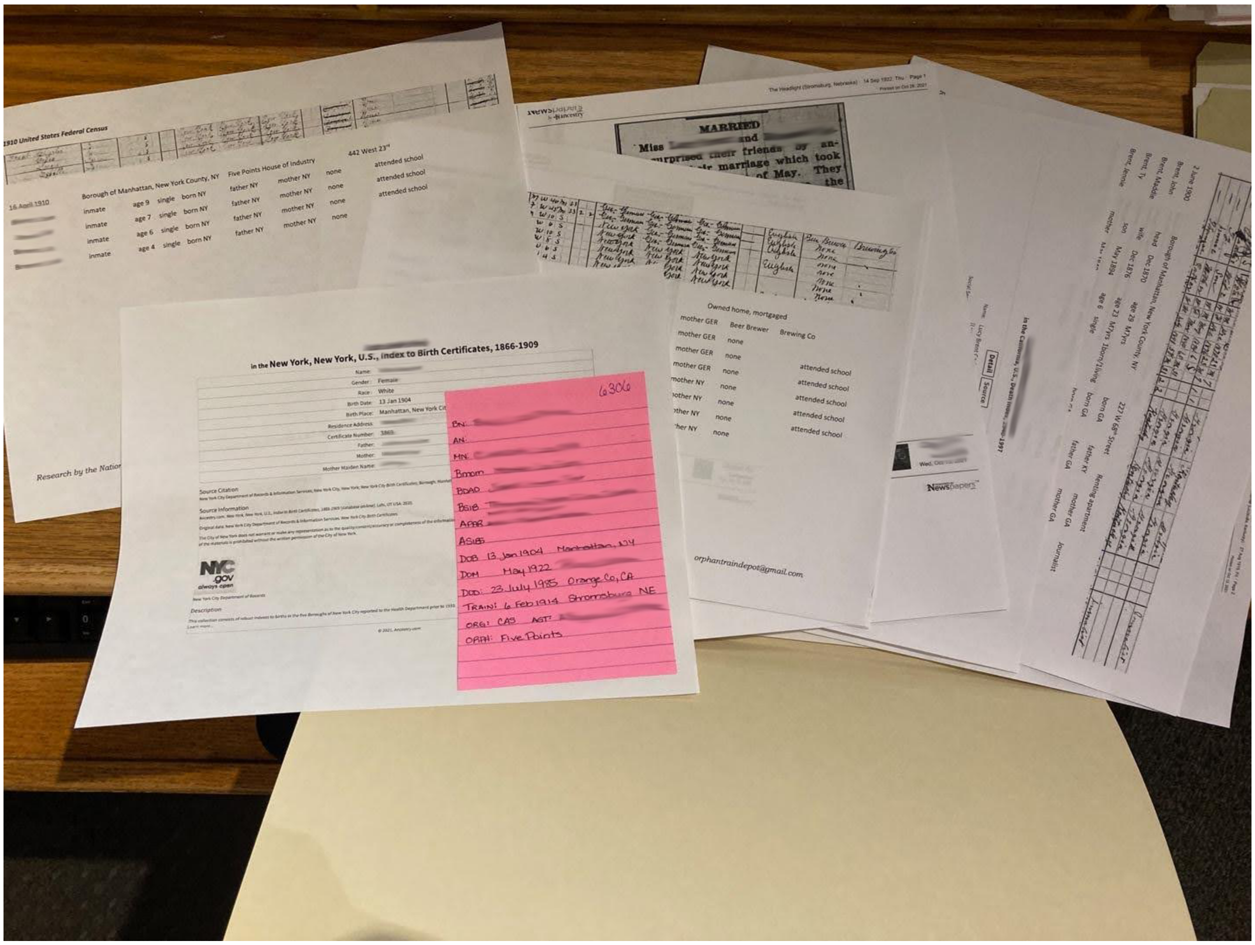

Figure A.3: Example of National Orphan Train Complex Research Document

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.

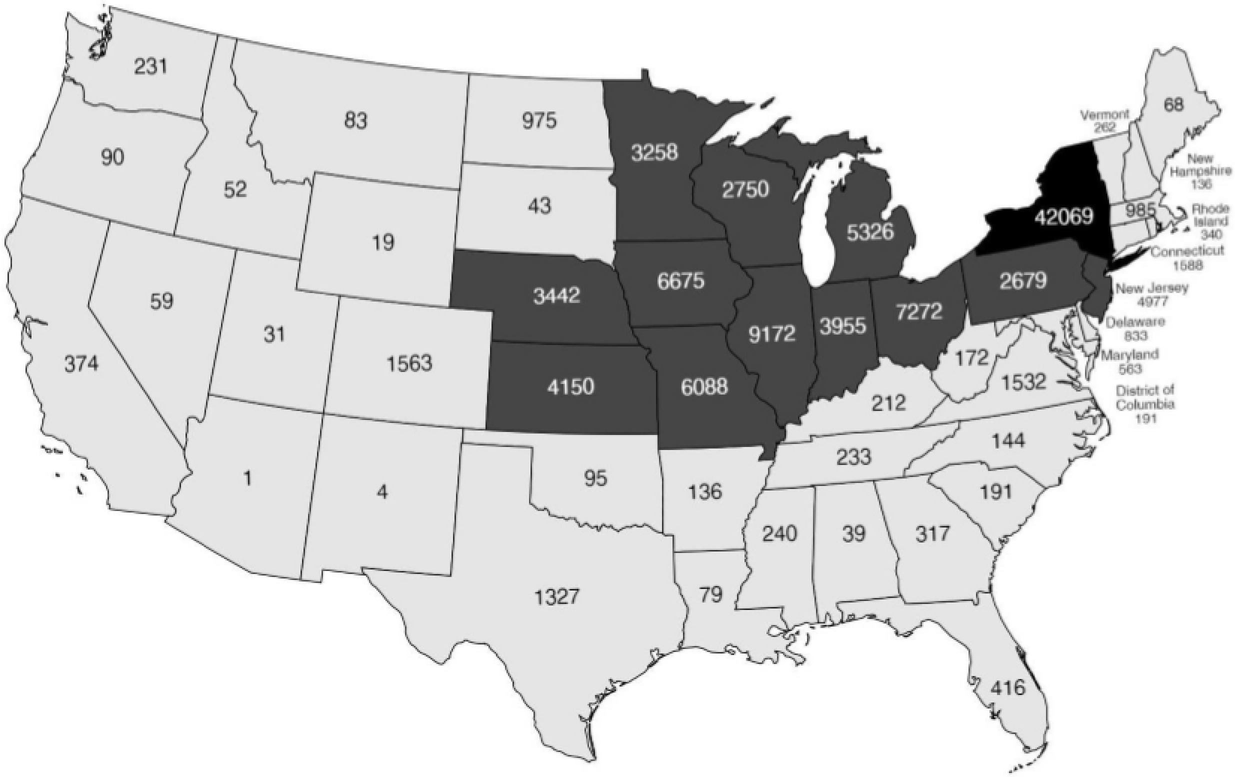

Figure A.5: Estimated Number of Child Placements Per State by the Children's Aid Society
Notes: Figure shows the estimated total geospatial distribution of rider destination locations across the United States by the largest participating orphanage the Children's Aid Society. Source: National Orphan Train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

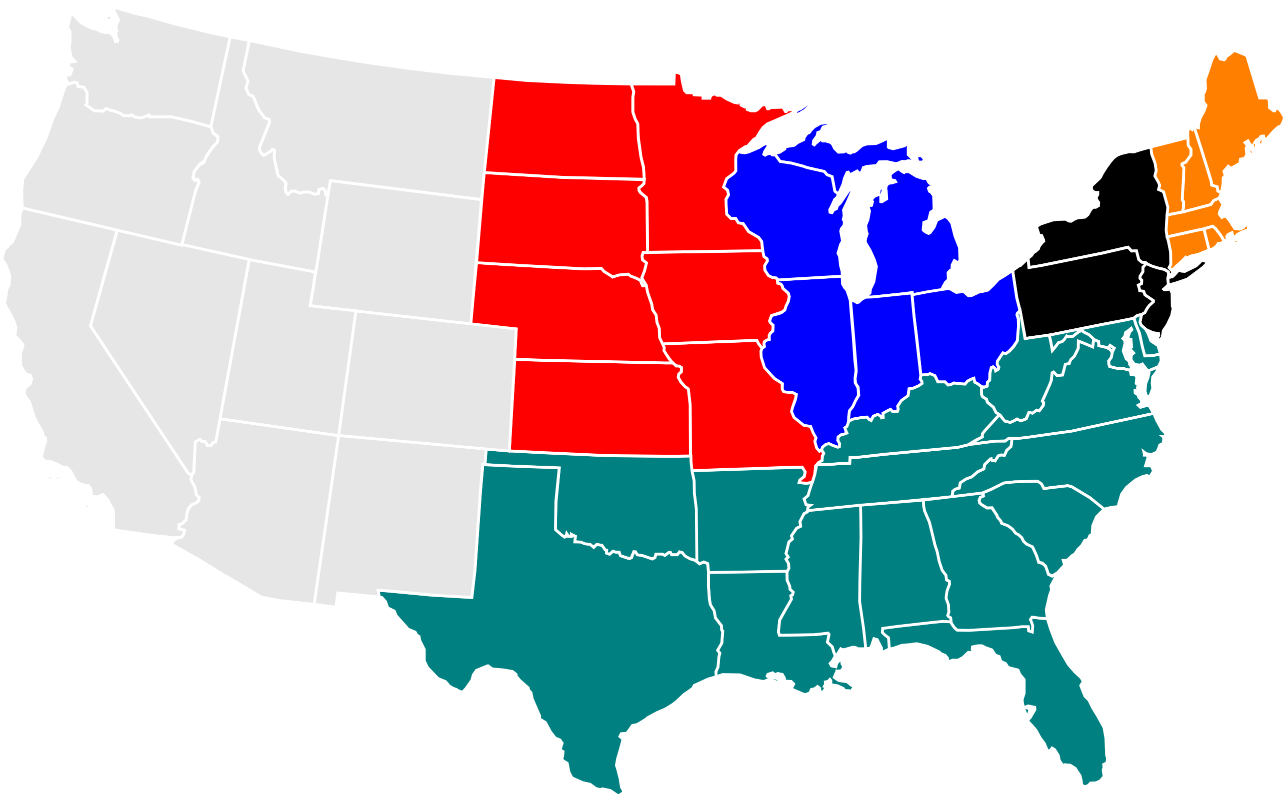

Figure A.6: Visualization of Geography Treatments

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 (1)	New England (2)	South (3)	West (4)	West Midwest (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: Age Heterogeneity on Place Effects: Interaction Specification

	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: This appendix presents an alternative specification testing age heterogeneity using interaction terms rather than the split-sample approach shown in Table 9. 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 A.13: Gender Heterogeneity in Place Effects: Interaction Specification

	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: This table presents an alternative specification using interaction terms to test for gender heterogeneity in place effects. Each column reports coefficients from OLS regressions. 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. High×Female is the interaction between being in high-opportunity county and being female. Demographic controls include age at placement, race, and immigrant status. Orphanage-place 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-opportunity counties. Results are consistent with the split-sample specification in Table 10, which reveals substantial gender heterogeneity masked by the interaction specification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: Time Period Heterogeneity in Place Effects: Interaction Specification

	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: This table presents an alternative specification using interaction terms to test for time period heterogeneity in place effects. 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 A.15: 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.16: 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 Principal Components and Factor Analysis For Combined Treatment

Our main analysis uses a binary opportunity index, defining counties as high-opportunity if they exceed the median on at least three of four characteristics (literacy, urbanicity, land value, population). To validate our preferred specification we conduct both factor analysis and principal components analysis (PCA) on the four standardized county characteristics.

Table B.1 reports component loadings from both methods. Factor loadings represent how each county characteristic reflects a latent opportunity construct, while PCA loadings show the weight of each variable in the first principal component. Examining the factor loading results reveal that urbanicity and population load most heavily on the opportunity dimension (0.692 and 0.667, respectively), while land value loads moderately (0.351) and literacy contributes minimally (0.123). This pattern follows closely in the PCA loadings (0.640, 0.621, 0.422, and 0.162, respectively), suggesting similar structures between factor and PCA treatments.

Table B.2 presents eigenvalues from both methods. The factor analysis eigenvalue captures the common variance shared across county characteristics. The factor eigenvalue of 1.062 justifies extracting one common factor. For PCA, the first principal component has an eigenvalue of 1.761, capturing 44.0% of the total variance in the four county characteristics. The second principal component has an eigenvalue of 0.985 (24.6% of variance), with the remaining components falling below the conventional threshold of 1.0 (Component 3: 0.833 or 20.8%; Component 4: 0.421 or 10.5%). The first two components jointly account for 68.7% of total variance. These results indicate that opportunity can be characterized by a single dimension, though some meaningful variation exists along a second dimension. The factor eigenvalue exceeding 1.0 confirms that extracting a single common factor is justified, aligning with our framework of constructing a combined opportunity measure.

Table B.3 validates our binary treatment approach by comparing it to continuous factor scores and the first principal component. Across all three outcomes the factor score and PCA yield statistically significant effects of similar magnitude to our main binary specification. This confirms that our binary classification effectively captures the underlying opportunity dimension and that our main results are robust to alternative specifications of the treatment.

Table B.1: Factor Analysis and PCA Component Loadings

	Factor Loading	PCA Loading
Literacy	0.123	0.162
Urbanicity	0.692	0.640
Land Value	0.351	0.422
Population	0.667	0.621

Notes: This table reports component loadings from factor analysis and principal components analysis (PCA) of the four standardized county characteristics. All variables are standardized to mean zero and standard deviation one prior to analysis.

Table B.2: Eigenvalues from Factor Analysis and PCA

	Factor Eigenvalue	PCA Eigenvalue
Component 1	1.062	1.761
Component 2	x	0.985
Component 3	x	0.833
Component 4	x	0.421

Notes: This table reports eigenvalues from factor analysis and principal components analysis. Factor analysis was conducted with one factor extraction, so only Component 1 has a factor eigenvalue. PCA eigenvalues are reported for all four components.

Table B.3: Factor Analysis and PCA on First Generation Outcomes

	Occ. Income Score		Number of Children		Ever Farmer	
	(1)	(2)	(3)	(4)	(5)	(6)
Factor Score	1.158***		-0.089***		-0.055***	
	(0.336)		(0.029)		(0.007)	
PCA Score		1.053***		-0.081***		-0.050***
		(0.357)		(0.027)		(0.007)
Observations	3,450	3,450	3,450	3,450	3,450	3,450
Control Mean	41.67	41.67	2.648	2.648	0.492	0.492
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays the results of alternative treatment definitions. Column 1 uses a single factor score from factor analysis on all four standardized county characteristics. Column 2 uses the first principal component from PCA. All specifications include demographic controls (age at placement, gender, race, immigrant status) and orphanage-by-placement-year fixed effects. Standard errors clustered at the county-census year level in parentheses. All three approaches yield statistically significant effects, confirming the validity of the binary classification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Alterative Specifications to Individual and Horse-Race Estimation

This section presents robustness checks using alternative treatment specifications and addressing potential concerns about interaction effects in the horse-race specification among our four county characteristics.

Table C.1 reports pairwise correlations among the four binary treatment indicators. Urbanicity and population exhibit moderate positive correlation (0.492), as do land value with both urbanicity (0.425) and population (0.387). Literacy shows weak correlations with other characteristics.

Tables C.2 and C.3 directly tests the robustness of our horse race results by comparing the standard specification with long regressions that sequentially add all possible interaction terms. For first generation outcomes (Table C.2) a pattern emerges such that although coefficients on the significant characteristics in the short (horse-race) specification remain similar in size and direction in the long (full-interaction) specification, we lose statistical significance due to lack of power. In the second generation outcomes (Table C.3) we see similar results but maintain statistical significance among urbanicity and land value for some outcomes.

Tables C.4, C.5, and C.6 seek to validate our binary treatment approach by replicating Tables 7, 8, and 9 using continuous standardized measures of each county characteristic. Coefficients now represent the effect of a one standard deviation increase in each treatment. The results reflect our main findings: urbanicity and population consistently predict better outcomes across both generations, while literacy shows minimal effects. In the income specification (Table C.4), a one standard deviation increase in urbanicity significantly raises first generation income by 1.71 points and population raises it by 1.06 points. Similar patterns emerge for fertility (Table C.5) and farming outcomes (Table C.6). The horse race specifications (Column 5) confirm that urbanicity and population remain the dominant pre-

Table C.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 **.

dictors when all characteristics compete simultaneously, validating our binary classification approach and demonstrating that our main results are robust to alternative functional forms.

Table C.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 C.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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Effects of Place on Average Income - Continuous Specification

	Average Occupational Income Score				
	(1)	(2)	(3)	(4)	(5)
Panel A: First Generation					
Literacy	0.597				0.480
	(0.423)				(0.422)
Urbanicity		1.709***			1.548***
		(0.381)			(0.495)
Land Value			0.141		-0.154
			(0.280)		(0.182)
Population				1.062**	0.228
				(0.482)	(0.460)
Observations	3,470	3,470	3,450	3,470	3,450
Overall Mean	43.322	43.322	43.322	43.322	43.322
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Second Generation					
Literacy	0.875				0.723
	(0.807)				(0.783)
Urbanicity		1.425***			0.963
		(0.483)			(0.760)
Land Value			0.792		-0.534
			(0.692)		(0.623)
Population				1.385***	0.848
				(0.452)	(0.692)
Observations	3,053	3,053	3,040	3,053	3,040
Overall Mean	44.586	44.586	44.586	44.586	44.586
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table replicates Table 6 using continuous standardized measures of county characteristics rather than binary above/below median indicators. All county characteristics are standardized to have mean zero and standard deviation one, so coefficients represent the effect of a one standard deviation increase in each characteristic. Panel A reports results for Generation 1 (Orphan Train riders). Panel B reports results for Generation 2 (children of riders). Columns (1)-(4) show results for each treatment individually. Column (5) includes all four treatments simultaneously in a horse race specification. All specifications include demographic controls (age at placement for Gen 1, gender, race, and immigrant status) and orphanage-by-placement-year fixed effects. Standard errors are clustered at the county-census year level and displayed in parentheses. Overall mean refers to the sample average of the outcome variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: Effects of Place on Fertility - Continuous Specification

	Number of Children				
	(1)	(2)	(3)	(4)	(5)
Panel A: First Generation					
Literacy	-0.058				-0.047
	(0.043)				(0.043)
Urbanicity		-0.138***			-0.124**
		(0.043)			(0.054)
Land Value			-0.009		0.014
			(0.015)		(0.016)
Population				-0.078***	-0.012
				(0.028)	(0.029)
Observations	3470	3470	3450	3470	3450
Overall Mean	2.474	2.474	2.474	2.474	2.474
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Second Generation					
Literacy	-0.069				-0.052
	(0.051)				(0.050)
Urbanicity		-0.126***			-0.105**
		(0.034)			(0.048)
Land Value			-0.043		0.064**
			(0.027)		(0.030)
Population				-0.110***	-0.048
				(0.031)	(0.046)
Observations	3,194	3,194	3,194	3,194	3,059
Overall Mean	1.776	1.776	1.776	1.776	1.776
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table replicates Table 7 using continuous standardized measures of county characteristics rather than binary above/below median indicators. All county characteristics are standardized to have mean zero and standard deviation one, so coefficients represent the effect of a one standard deviation increase in each characteristic. Panel A reports results for Generation 1 (Orphan Train riders). Panel B reports results for Generation 2 (children of riders). Columns (1)-(4) show results for each treatment individually. Column (5) includes all four treatments simultaneously in a horse race specification. All specifications include demographic controls (age at placement for Gen 1, gender, race, and immigrant status) and orphanage-by-placement-year fixed effects. Standard errors are clustered at the county-census year level and displayed in parentheses. Overall mean refers to the sample average of the outcome variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.6: Effects of Place on Farming - Continuous Specification

	Ever Worked in Farming				
	(1)	(2)	(3)	(4)	(5)
Panel A: First Generation					
Literacy	-0.001				0.006
	(0.010)				(0.009)
Urbanicity		-0.077***			-0.070***
		(0.008)			(0.011)
Land Value			-0.022**		-0.009*
			(0.010)		(0.005)
Population				-0.046***	-0.009
				(0.007)	(0.007)
Observations	3,470	3,470	3,450	3,470	3,450
Overall Mean	0.443	0.443	0.443	0.443	0.443
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes
Panel B: Second Generation					
Literacy	-0.010				-0.003
	(0.020)				(0.018)
Urbanicity		-0.065***			-0.050***
		(0.010)			(0.015)
Land Value			-0.057***		-0.009
			(0.017)		(0.013)
Population				-0.061***	-0.020
				(0.009)	(0.014)
Observations	3,470	3,470	3,450	3,470	3,450
Overall Mean	0.352	0.352	0.352	0.352	0.352
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Orphanage-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table replicates Table 8 using continuous standardized measures of county characteristics rather than binary above/below median indicators. All county characteristics are standardized to have mean zero and standard deviation one, so coefficients represent the effect of a one standard deviation increase in each characteristic. Panel A reports results for Generation 1 (Orphan Train riders). Panel B reports results for Generation 2 (children of riders). Columns (1)-(4) show results for each treatment individually. Column (5) includes all four treatments simultaneously in a horse race specification. All specifications include demographic controls (age at placement for Gen 1, gender, race, and immigrant status) and orphanage-by-placement-year fixed effects. Standard errors are clustered at the county-census year level and displayed in parentheses.Overall mean refers to the sample average of the outcome variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Analysis on Native Children

Table D.1 addresses potential concerns about balance on pre-determined characteristics by restricting the sample to native-born riders only. While Table A.5 shows that some individual treatments fail joint balance tests when including all riders (with F-statistics ranging from 1.25 to 4.70), restricting to natives substantially improves balance. In Table D.1, the F-statistics drop considerably for most treatments: literacy (5.04 to 1.04), urbanicity (2.13 to 1.06), and population (8.71 to 0.31) all fail to reject the null of joint balance in specifications with fixed effects. Land value remains marginally significant (F=4.80), though the effect is driven primarily by the white indicator rather than placement age or gender. The improvement in balance among native-born riders likely reflects differences in placement patterns driven by immigration shocks. Non-native children arrived at orphanages in waves corresponding to major immigration surges, creating cohorts that flooded institutions within concentrated time periods. When only a few trains operated in a given year, these immigrant-heavy cohorts may have been systematically sent to particular types of destinations, creating imbalance. Our preferred specification is to keep non-native children in the main analysis as they are an important feature of the orphan train movement.

Table D.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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Model of Place Capital Formation and Age Heterogeneity

We develop a simple model of place capital formation to understand how placement age affects the returns to high-opportunity locations. Consider that average income earned during adulthood is a function of accumulated place capital:

$$Y_i = \omega(PC_i) \tag{12}$$

where $\omega(\cdot)$ is a strictly increasing concave function reflecting diminishing marginal returns to place capital investment (Ben-Porath, 1967), and PC_i represents the place capital accumulated by rider i.

Place capital for a rider i is determined by two sequential treatments:

$$PC_i = PC_0 + \Delta_1 Young_i + \Delta_2 T_i + \Delta_3 Young_i \times T_i \tag{13}$$

where PC_0 is baseline place capital for orphaned children in NYC during the sample period. Δ_1 is the additional place 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 place 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 place capital acquired by the interaction of being placed young and in a high-opportunity area.

Children are placed based on their relative arrival to the orphanage. We assume that placement through the Orphan Train resulted in, on average, higher levels of place 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:

$$\tau_{young} = \underbrace{\omega(PC_0 + \Delta_1 + \Delta_2 + \Delta_3)}_{\text{high-opportunity county}} - \underbrace{\omega(PC_0 + \Delta_1)}_{\text{low-opportunity county}} \tag{14}$$

for young riders, and

$$\tau_{old} = \underbrace{\omega(PC_0 + \Delta_2)}_{\text{high-opportunity county}} - \underbrace{\omega(PC_0)}_{\text{low-opportunity county}} \tag{15}$$

for old riders. The model generates predictions about the relationship between place capital accumulation and income effects. While younger children accumulate larger absolute gains in place capital from high-opportunity counties ($\Delta_2 + \Delta_3 > \Delta_2$) due to longer exposure, they experience these gains along a flatter portion of the concave income function because they begin from a higher baseline ($PC_0 + \Delta_1$ versus PC_0). The degree of concavity in $\omega(\cdot)$ and the magnitude of Δ_1 jointly determine the observed relationship between treatment effects neither of which we directly observe in our data. We could observe $\tau_{young} > \tau_{old}$ if exposure effects in place capital accumulation dominate, $\tau_{old} > \tau_{young}$ if diminishing returns dominate, or $\tau_{young} \approx \tau_{old}$ if these forces approximately offset. Figure E.1 illustrates this framework showing diminishing returns dominating.

This theoretical framework generates nuanced predictions about age heterogeneity in observed income effects. While younger children accumulate larger absolute gains in place capital from high-opportunity counties ($\Delta_2 + \Delta_3 > \Delta_2$) due to longer exposure, consistent with Chetty et al. (2016), they experience these gains along a flatter portion of the concave income function $\omega(\cdot)$ because they begin from a higher baseline ($PC_0 + \Delta_1$ versus PC_0). Conversely, older children accumulate smaller absolute place capital gains but experience them along a steeper portion of the income function where marginal returns are higher.

The mapping from place capital to income may therefore produce similar income effects even when place capital accumulation differs substantially by age. Formally, this occurs when:

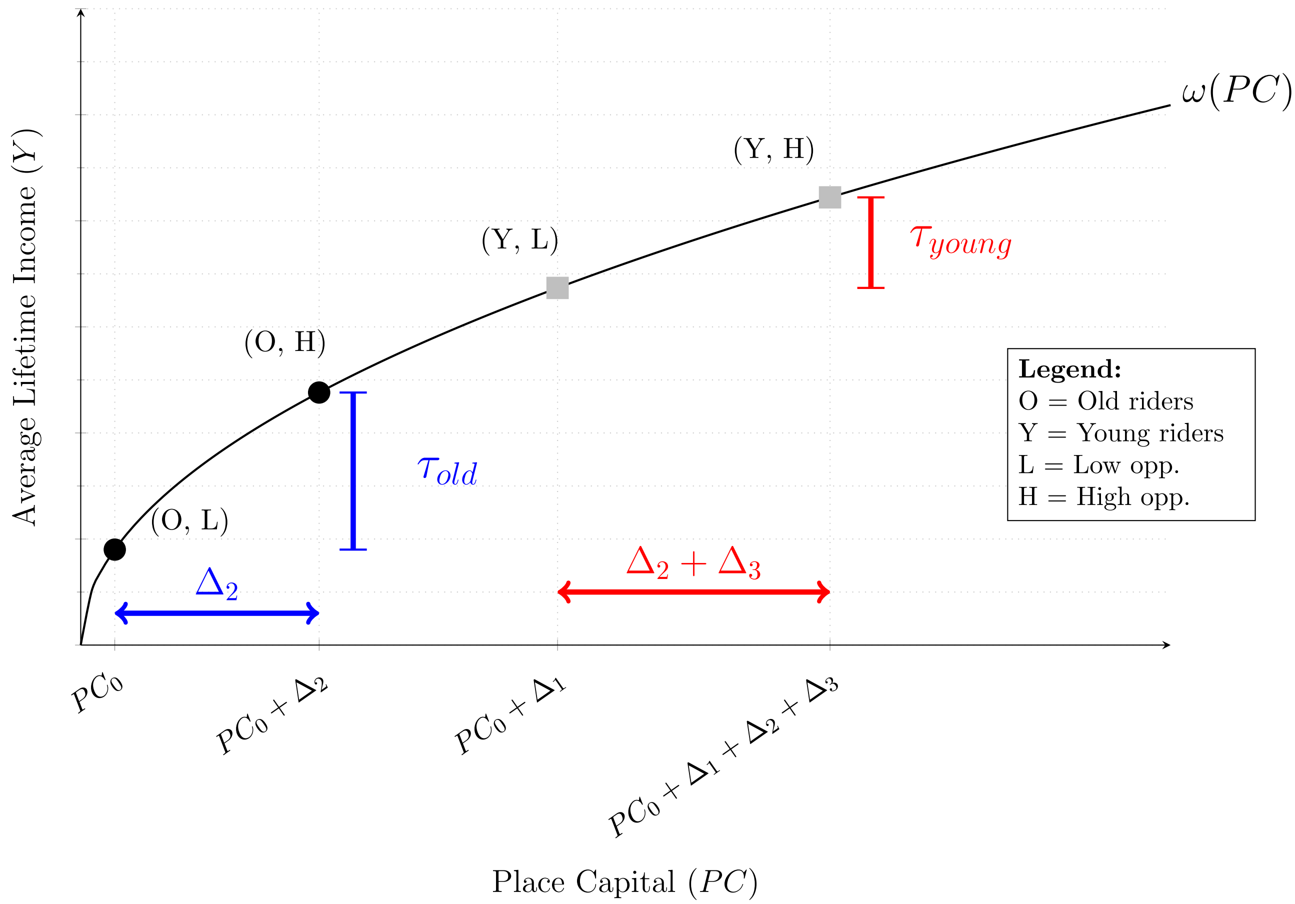

Figure E.1: Visualization of Age Heterogeneity Effects

Notes: This figure illustrates the theoretical framework for age heterogeneity in place effects. The concave function $\omega(PC)$ maps place 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 place capital PC_0; (O, H) = old rider in high-opportunity county with place capital $PC_0+\Delta_2$; (Y, L) = young rider in low-opportunity county with place capital $PC_0+\Delta_1$; (Y, H) = young rider in high-opportunity county with place capital $PC_0+\Delta_1+\Delta_2+\Delta_3$. Here Δ_1 represents additional place capital from early placement, Δ_2 represents place capital gains from high-opportunity locations, and Δ_3 captures the interaction between young age and high-opportunity placement. The horizontal arrows show place 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 place capital from better places ($\Delta_2 + \Delta_3 > \Delta_2$), may experience different marginal income gains depending on the degree of concavity. The figure illustrates a case where diminishing returns dominate, $\tau_{young} < \tau_{old}$. Empirically, we observe approximately equal effects, $\tau_{young} \approx \tau_{old}$, consistent with offsetting exposure effects and diminishing returns.

$$\omega(PC_0 + \Delta_1 + \Delta_2 + \Delta_3) - \omega(PC_0 + \Delta_1) \approx \omega(PC_0 + \Delta_2) - \omega(PC_0) \tag{16}$$

despite $(\Delta_2 + \Delta_3) > \Delta_2$. Our point estimates in Table 10 show similar income effects for younger (2.74 percentile points) and older children (2.44 percentile points), with overlapping confidence intervals, consistent with approximate offsetting of exposure effects and diminishing returns.

This framework suggests that exposure effects operate as expected at the level of place capital formation, younger children do accumulate more advantages from longer exposure to high-opportunity counties, but the concave income production function reduces these differences when translated into observed earnings. The observed heterogeneity in farming propensity (-12.1 versus -7.4 percentage points) supports this interpretation, as occupational choice may respond more linearly to place capital than income does, preserving the exposure effect pattern found in the MTO literature.

This finding extends the MTO literature by demonstrating that the absence of clear age heterogeneity in income effects does not imply the absence of exposure effects in place capital accumulation. Rather, it highlights that income effects reflect both the accumulation of advantages and their translation into earnings through a capital accumulation. Understanding this distinction is important for interpreting place effects research, as interventions may generate substantial gains in capital that are only partially reflected in measured income outcomes.