Migration Networks and Location Decisions: Evidence from U.S. Mass Migration*

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Abstract

This paper studies how birth town migration networks affect long-run location decisions. We develop a new method to estimate the strength of migration networks for each receiving and sending location. Our estimates imply that when one randomly chosen African American moved from a Southern birth town to a destination county, then 1.9 additional black migrants made the same move on average. For white migrants from the Great Plains, the average is only 0.4. Networks were particularly important in connecting black migrants with attractive employment opportunities and played a larger role in less costly moves.
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1 Introduction

Theoretical and empirical research emphasizes the role of expected real wages, amenities, and moving costs in individuals' location decisions (Sjaastad, 1962; Greenwood, 1997; Kennan and Walker, 2011). While theory suggests that social networks might matter as well (Carrington, Detragiache and Vishwanath, 1996), estimating the importance of this factor has proven difficult because of a lack of suitable data sets and research designs. For example, it is well known that immigrants from the same country tend to live in the same place, but this fact does not distinguish between the role of social networks and numerous common factors, such as moving costs, human capital, and language. Evidence on the effects of social networks on location decisions would inform our understanding of past and future migration episodes, the equilibration of local labor markets, and the impacts of policies that affect migration incentives. Furthermore, social networks might continue to attract migrants to their chosen destination for many years, thus limiting adjustments as economic conditions change, and ultimately contributing to spatial mismatch.

This paper provides new evidence on the effects of social networks on location decisions. We focus on the mass migrations in the mid-twentieth century of African Americans from the U.S. South and whites from the Great Plains. We proxy for social networks using birth towns, which are particularly relevant in this setting, and we use administrative data that measure town of birth and county of residence at old age for most of the U.S. population born from 1916-1936. Our setting and data provide a unique opportunity to study the long-run effects of migration networks. We use detailed geographic information to distinguish the effect of birth town migration networks from other determinants of location decisions, such as moving costs determined by geography or railroad lines. For example, we observe that 51 percent of African American migrants born from 1916-1936 in Pigeon Creek, Alabama moved to Niagara County, New York, while less than six percent of black migrants from nearby towns moved to the same county. This comparison underlies our research design, which asks whether individuals born in the same town are more likely to live in the same destination in old age than individuals born in nearby towns.

We combine this transparent research design with a new method of characterizing birth town migration networks. Our new parameter, which we call the network index, allows us to estimate the effect of migration networks on location decisions for each receiving and sending location and then relate these estimates to locations' economic characteristics. We show that existing methods may mischaracterize the effect of migration networks in our setting. In particular, the influential approach of Bayer, Ross and Topa (2008) could estimate strong effects for popular destinations even if true effects are relatively weak, and as a result could misstate the overall effect of networks. Our method does not suffer from this problem. Under straightforward and partly testable assumptions, the network index identifies the effect of birth town migration networks and maps directly to structural network models.

We find that migration networks strongly influenced the location decisions of Southern black migrants. Our estimates imply that when one randomly chosen African American moves from a birth town to a destination county, then 1.9 additional black migrants make the same move on average. Migration networks drew African Americans to destinations with a higher share of 1910 employment in manufacturing, a particularly attractive sector for black workers in our sample. This evidence highlights an important role for migration networks in providing job referrals or information about employment opportunities. We also find that networks drew black migrants to destinations that were closer and more connected by railroads, pointing to the importance of access to information and low moving costs in the functioning of these networks. In addition, networks are stronger in sending counties with higher literacy rates in 1920, suggesting that education and related factors facilitated network development.

We estimate weaker effects of migration networks on the location decisions of whites. For migrants from the Great Plains, our results imply that when one randomly chosen migrant moves from a birth town to a destination county, then 0.4 additional white migrants make the same move on average. Results for Southern white migrants are similarly small. Furthermore, migration networks among whites are less sensitive to employment opportunities and moving costs. There are many possible explanations for the different effects of networks on black and white migrants. Given the myriad unobserved differences between these groups, this paper does not attempt to explain the black-white gap. However, one explanation supported by historical context and our results is that black migrants relied more heavily on their networks to overcome discrimination in labor and housing markets and a lack of financial resources.

To further study the role of migration networks, we map the network index to a structural model that generalizes the model in Glaeser, Sacerdote and Scheinkman (1996). We estimate that 34 percent of Southern black migrants and 13 percent of Great Plains white migrants chose their long-run destination because of migration networks. In the absence of networks, Chicago would have 29 percent fewer Southern black migrants, and Los Angeles, Detroit, Philadelphia, and Baltimore would have 11 to 25 percent fewer black migrants. Eliminating migration networks would reduce the number of Great Plains white migrants in several places in California, including Los Angeles, Bakersfield, and Fresno. While our model does not account for all possible general equilibrium effects, the direction of these effects is not clear: reducing migration from a town to a county could make that destination more attractive, because of higher wages or lower housing costs, or less attractive, because of fewer individuals with a similar background. Still, the model suggests that migration networks had important effects on the U.S. population distribution.

We use the structural model to examine whether migrants would live in destinations with better economic opportunities in the absence of networks, as could occur if networks contributed to spatial mismatch. In the absence of migration networks, Southern black migrants would live in counties with a slightly smaller African American population share, unemployment rate, and poverty rate, while Great Plains white migrants would live in counties that are nearly identical. Migration networks have little effect on destination characteristics because migrants that did not follow their network moved to similar destinations.

Several pieces of evidence support the validity of our empirical strategy. Our research design, which compares the location decisions of migrants from nearby towns, implies that destination-level network index estimates should not change when controlling for birth town characteristics, because geographic proximity controls for the relevant determinants of location decisions. Reassuringly, our estimates are essentially unchanged when adding several covariates. We also estimate strong network effects in certain locations, like Rock County, Wisconsin, for which qualitative work supports our findings (Bell, 1933; Rubin, 1960; Wilkerson, 2010).

This paper makes three contributions. First, we develop a new method of characterizing migration networks. Our approach integrates previous work by Glaeser, Sacerdote and Scheinkman (1996) and Bayer, Ross and Topa (2008), has desirable theoretical and statistical properties, and can be used to study networks in other settings and for outcomes besides migration. Second, we provide new evidence on the importance of birth town migration networks and the types of individuals and economic conditions for which networks are most important.[1] Previous work shows that individuals tend to migrate to the same place, often broadly defined, as other individuals from the same town or country, but does not isolate the role of social networks in the decision of where to move (Bartel, 1989; Bauer, Epstein and Gang, 2005; Beine, Docquier and Ozden, 2011; Giuletti, Wahba and Zenou, 2014; Spitzer, 2016).[2] Third, our results inform landmark migration episodes that have drawn interest from economists for a century (Scroggs, 1917; Smith and Welch, 1989; Margo, 1990; Carrington, Detragiache and Vishwanath, 1996; Collins, 1997; Boustan, 2009, 2010; Hornbeck, 2012; Hornbeck and Naidu, 2014; Black et al., 2015; Collins and Wanamaker, 2015; Johnson and Taylor, 2016; Long and Siu, 2018). Our results complement the small number of interesting but unrepresentative historical accounts suggesting that networks were important in these migration episodes (Jamieson, 1942; Rubin, 1960; Gottlieb, 1987; Gregory, 1989).

Our paper also complements recent work by Chay and Munshi (2015). They find that, above a threshold, migrants born in counties with higher population density tend to move to fewer locations, as measured by a Herfindahl-Hirschman Index, and show that this non-linear relationship accords with a network formation model with fixed costs of participation. We also find some evidence that networks were stronger in denser sending communities. We differ in our research design, empirical methodology, study of white migrants, examination of how network effects vary

[1]This complements research on the effects of social networks on labor market outcomes (e.g., Topa, 2001; Munshi, 2003; Ioannides and Loury, 2004; Bayer, Ross and Topa, 2008; Hellerstein, McInerney and Neumark, 2011; Beaman, 2012; Burks et al., 2015; Schmutte, 2015; Heath, 2016). These papers do not focus on the formation of social networks, which in some cases, like Munshi (2003), arise from location decisions.

[2]One exception is Chen, Jin and Yue (2010), who study the impact of peer migration on temporary location decisions in China. However, they lack detailed geographic information on where individuals move.

across destinations, and use of a structural model to examine counterfactuals.

2 Historical Background on Mass Migration Episodes

The Great Migration saw nearly six million African Americans leave the South from 1910 to 1970 (Census, 1979). Although migration was concentrated in certain destinations, like Chicago, Detroit, and New York, other cities also experienced dramatic changes. For example, Chicago's black population share increased from two to 32 percent from 1910-1970, while Racine, Wisconsin experienced an increase from 0.3 to 10.5 percent (Gibson and Jung, 2005). Migration out of the South increased from 1910-1930, slowed during the Great Depression, and then resumed forcefully from 1940 to 1970.

Several factors contributed to the exodus of African Americans from the South. World War I, which simultaneously increased labor demand among Northern manufacturers and decreased labor supply from European immigrants, helped spark the Great Migration, although many underlying causes existed long before the war (Scroggs, 1917; Scott, 1920; Gottlieb, 1987; Marks, 1989; Jackson, 1991; Collins, 1997; Gregory, 2005). These causes include a less developed Southern economy, the decline in agricultural labor demand due to the boll weevil's destruction of cotton crops (Scott, 1920; Marks, 1989, 1991; Lange, Olmstead and Rhode, 2009), widespread labor market discrimination (Marks, 1991), and racial violence and unequal treatment under Jim Crow laws (Tolnay and Beck, 1991).

Migrants tended to follow paths established by railroad lines. For example, Mississippi-born migrants predominantly moved to Illinois and other Midwestern states, and South Carolina-born migrants predominantly moved to New York and Pennsylvania (Scott, 1920; Carrington, Detragiache and Vishwanath, 1996; Collins, 1997; Boustan, 2010; Black et al., 2015). Labor agents, offering paid transportation, employment, and housing, directed some of the earliest migrants, but historical accounts suggest that their role diminished sharply after the 1920s and most individuals paid for the expensive train fares themselves (Gottlieb, 1987; Grossman, 1989).[3] African American

[3]In 1918, train fare from New Orleans to Chicago cost $22 per person, when Southern farmers' daily wages

newspapers from the largest destinations circulated throughout the South, providing information on life in the North (Gottlieb, 1987; Grossman, 1989).[4]

A small number of historical accounts suggest a role for migration networks in location decisions. Social networks, consisting primarily of family, friends, and church members, sometimes provided valuable job references or shelter (Scott, 1920; Rubin, 1960; Gottlieb, 1987). For example, Rubin (1960) finds that migrants from Houston, Mississippi had close friends or family at two-thirds of all initial destinations.[5] These accounts emphasize interactions between individuals from the same birth town, which motivates our focus on birth town migration networks.

The experience of John McCord captures many important features of early black migrants' location decisions.[6] Born in Pontotoc, Mississippi, nineteen-year-old McCord traveled in search of higher wages in 1912 to Savannah, Illinois, where a fellow Pontotoc-native connected him with a job. McCord moved to Beloit, Wisconsin in 1914 after hearing of employment opportunities and quickly began working as a janitor at the manufacturer Fairbanks Morse and Company. After two years in Beloit, McCord spoke to his manager about returning home for a vacation. The manager asked McCord to recruit workers during the trip, and McCord returned with 18 unmarried men, all of whom were soon hired. Thus began a persistent flow of African Americans from Pontotoc to Beloit: among individuals born from 1916-1936, 14 percent of migrants from Pontotoc lived in Beloit's county in old age (Table 2, discussed below).

Migration out of the Great Plains has received less academic attention than the Great Migration, but nonetheless represents a landmark reshuffling of the U.S. population. Considerable out-migration from the Great Plains started around 1930 (Johnson and Rathge, 2006). Explanations for the out-migration include the decline in agricultural prices due to the Great Depression, a drop in agricultural productivity due to drought, and the mechanization of agriculture (Gregory, 1989; Curtis White, 2008; Hurt, 2011; Hornbeck, 2012). Some historical work points to an important

typically were less than $1 and wages at Southern factories were less than $2.50 (Henri, 1975).

[4]The *Chicago Defender*, perhaps the most prominent African American newspaper of the time, was read in 1,542 Southern towns and cities in 1919 (Grossman, 1989).

[5]Rubin (1960) studied individuals from Houston, Mississippi because so many migrants from Houston moved to Beloit, Wisconsin. While interesting, this sample is clearly not representative.

[6]The following paragraph draws on Bell (1933). See also Knowles (2010).

role for migration networks (Jamieson, 1942; Gregory, 1989). For example, Jamieson (1942) finds that almost half of migrants to Marysville, California had friends or family living there.

The mass migrations out of the South and Great Plains share several features. In both episodes, millions of people made long-distance moves in search of better economic and social opportunities. Both episodes occurred around the same time and saw a similar share of the population undertake long-distance moves, as we describe below. In addition, both African American and white migrants experienced discrimination in many destinations, although African Americans faced far more severe discrimination and had less wealth (Gregory, 2005).

3 Estimating the Effects of Migration Networks on Location Decisions

3.1 Data on Location Decisions

To measure location decisions, we use the Duke University SSA/Medicare data, which covers over 70 million individuals who received Medicare Part B from 1976-2001. The data contain race, sex, date of birth, date of death (if deceased), and the ZIP code of residence at old age (death or 2001, whichever is earlier). In addition, the data include a 12-character string with self-reported birth town information, which is matched to places, as described in Black et al. (2015). We use the data to measure long-run migration flows from birth town to destination county for individuals born from 1916-1936.[7] This sample lies at the center of both episodes, and the 1916-1936 cohorts have among the highest out-migration rates (Appendix Figure A.1). As seen in Figure 1, which we construct using repeated cross sections of decennial census data, the vast majority of Southern black and Great Plains white migrants born from 1916-1936 migrated between 1940 and 1960. Most of these migrants were 15-35 years old when they moved (Appendix Figure A.2). To improve the reliability of our estimates, we restrict the sample to birth towns with at least ten migrants and, separately for each birth state, combine all destination counties with less than ten migrants.

Figure 2 displays the states we include in the South and Great Plains. For migration out of

[7] Our sample begins with the 1916 cohort because coverage rates are low for prior years (Black et al., 2015) and ends with 1936 because that is the last cohort available in the data.

the South, we study individuals born in Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, and South Carolina. We define a migrant as someone who moved out of the 11 former Confederate states.[8] For migration out of the Great Plains, we study individuals born in Kansas, Nebraska, North Dakota, Oklahoma, and South Dakota. We define a migrant as someone who moved out of the Great Plains and a border region, shaded in light grey in Panel B.[9] We make these choices to focus on the long-distance moves that characterize both migration episodes.

Our data capture long-run location decisions, as we only observe individuals' location at birth and old age. We cannot identify return migration: if an individual moved from Mississippi to Wisconsin, then returned to Mississippi at age 60, we do not identify that person as a migrant. It would be interesting to examine short- and medium-run location decisions, but unfortunately the available data do not allow this.[10] Still, the effect of social networks on long-run location decisions is of substantial interest. We also do not observe individuals who die before age 65 or do not enroll in Medicare. We discuss the implications of these measurement issues below.

3.2 Econometric Model: The Network Index

A natural starting point for an econometric model is the influential approach of Bayer, Ross and Topa (2008), which leverages detailed geographic data to identify the effects of networks. Extending their model to our setting yields

$$D_{i,j(i),k}D_{i',j(i'),k} = \alpha_{g,k} + \sum_{j\in g} \beta_{j,k} 1[j(i) = j(i') = j] + \epsilon_{i,i',k}, \quad (1)$$

[8]These include the seven states already listed, plus Arkansas, Tennessee, Texas, and Virginia.

[9]This border region includes Arkansas, Colorado, Iowa, Minnesota, Missouri, Montana, New Mexico, Texas, and Wyoming. We do not focus primarily on Dust Bowl migration. Our Great Plains states did experience soil erosion in the 1930s, but other states also experienced soil erosion (see Hornbeck, 2012), and the Southern Great Plains states of Colorado, Kansas, Oklahoma, and Texas are most associated with the Dust Bowl (Long and Siu, 2018).

[10]To study short-run location decisions, we linked individuals between the 1920 and 1940 complete count Censuses, as in Abramitzky, Boustan and Eriksson (2017). The resulting sample size was too small to generate reliable estimates. For example, of the 334,605 Southern black migrants in the 1940 Census, we were only able to use 18,312 migrants (5.5 percent) to estimate our network index. This low coverage rate is mainly due to our ability to match only 12.5 percent of Southern black migrants from the 1940 to 1920 Census (in line with the match rates for African Americans in Eriksson (2016)). The low coverage rate also stems from our exclusion of birth towns (Minor Civil Divisions in the Census) with fewer than 10 migrants. The coverage rate for whites from the Great Plains is also too low (8.4 percent) to generate reliable results.

where $D_{i,j,k} = 1$ if migrant i moves from birth town j to destination county k and $D_{i,j,k} = 0$ if migrant i moves elsewhere, $j(i)$ is the birth town of migrant i, and both i and i' live in birth town group g. As described below, we define birth town groups in two ways: counties and square grids independent of county borders. The fixed effect $\alpha_{g,k}$ equals the average propensity of migrants from birth town group g to co-locate in destination k, and $\beta_{j,k}$ equals the additional propensity of migrants from the same birth town j to co-locate in k.[11] Equation (1) allows location decision determinants to vary arbitrarily at the birth town group-by-destination level through $\alpha_{g,k}$ (e.g., because of differences in migration costs due to railroads or highways). The parameter of interest, $\beta_{j,k}$, is identified from within birth town group comparisons.

The parameters governing networks in this setting are the probability of moving to a destination and the covariance of location decisions among migrants from the same town. We denote the probability that a migrant born in town j chooses destination k as $P_{j,k} \equiv \mathbb{E}[D_{i,j,k}]$. This ex-ante probability reflects individuals' preferences, resources, and the expected return to migration, but does not depend on other individuals' realized location decisions. The average covariance of location decisions for two migrants from the same town is $C_{j,k} \equiv \sum_{i \neq i' \in j} \mathbb{C}[D_{i,j,k}, D_{i',j,k}]/(N_j(N_j-1))$.[12] The number of people who move from j to k is $N_{j,k} \equiv \sum_{i \in j} D_{i,j,k}$, and the number of migrants from birth town j is $N_j \equiv \sum_k N_{j,k}$.

To better understand the reduced-form in equation (1), we map the parameters of the extended Bayer, Ross and Topa (2008) model, $(\alpha_{g,k}, \beta_{j,k})$, into parameters governing social networks, $(P_{j,k}, C_{j,k})$. Doing so requires two assumptions. The most important assumption is that $P_{j,k}$ is constant across birth towns in the same group:

Assumption 1. $P_{j,k} = P_{j',k}$ for different birth towns in the same birth town group, $j \neq j' \in g$.

Assumption 1 formalizes the idea that there are no ex-ante differences across nearby birth

[11] Bayer, Ross and Topa (2008) study the propensity of workers that live in the same census block to work in the same census block, beyond the propensity of workers living in the same block group (a larger geographic area) to work in the same block. In their initial specification, $\alpha_{g,k}$ does not vary by k, and $\beta_{j,k}$ does not vary by j or k. In other specifications, they allow the slope coefficient to depend on observed characteristics of the pair (i, i').

[12] Glaeser, Sacerdote and Scheinkman (1996) use the "excess variance" of decisions to infer the presence of social networks. This approach is very closely related, as a positive covariance of decisions increases the variance (see also Graham, 2008). Brock and Durlauf (2001) and Blume et al. (2011) provide comprehensive discussions of the related topic of estimating social interactions.

towns in the value of moving to each destination. For example, this assumes away the possibility that migrants from Pigeon Creek, Alabama had preferences or human capital particularly suited for Niagara Falls, New York relative to migrants from a nearby town, such as Oaky Streak, which is six miles away. This assumption attributes large differences in realized moving propensities across nearby towns to migration networks.

Assumption 1 is plausible in our setting. Preferences for destination features, such as wages or climate, and information about destinations likely did not vary sharply across nearby birth towns. Furthermore, individuals tended to work in different industries after migrating (Appendix Table A.1), suggesting a negligible role for human capital specific to a destination county that differed across nearby birth towns. Conditional on migrating, the cost of moving to a given destination likely did not vary sharply across nearby towns.[13] We do not restrict the probability of moving from birth town group g to destination k, $P_{g,k}$, which allows destinations to vary in their attractiveness to migrants for myriad reasons.

Below, we describe evidence that supports the validity of Assumption 1. Most importantly, we show that using birth town covariates to explain moving probabilities does not affect network index estimates. This implies that geographic proximity adequately controls for the relevant determinants of location decisions, as embedded in Assumption 1. In addition, our results are similar for individuals born from 1916-25 and 1926-1936; the latter group was much less likely to serve in World War II, which suggests that our results are not driven by networks formed in the military.

The second assumption is that migrants' location decisions are not influenced by migrants from other birth towns:

Assumption 2. $\mathbb{C}[D_{i,j,k}, D_{i',j',k}] = 0$ for migrants from different birth towns, $j \neq j'$.

Assumption 2 allows us to map the parameters of the extended Bayer, Ross and Topa (2008) model, $(\alpha_{g,k}, \beta_{j,k})$, into the parameters governing social networks, $(P_{j,k}, C_{j,k})$. Migration networks that extend across nearby towns, which violate Assumption 2, would lead us to underestimate the effect of birth town migration networks.

[13] Assumption 1 is not violated if the cost of moving to all destinations varied sharply across birth towns (e.g., because of proximity to a railroad), as we focus on where people move, conditional on migrating.

Under Assumptions 1 and 2, the slope coefficient in equation (1) equals the covariance of location decisions from birth town j to destination k: $\beta_{j,k} = C_{j,k}$.[14] In addition, the fixed effect in equation (1) equals the squared moving probability: $\alpha_{g,k} = P^2_{g,k}$. This analysis demonstrates that the Bayer, Ross and Topa (2008) model uses the covariance of decisions to measure the effect of networks.

In certain settings, the Bayer, Ross and Topa (2008) model could mischaracterize the effect of networks. To see this, let $\mu_{j,k} \equiv \mathbb{E}[D_{i,j,k}|D_{i',j,k} = 1]$ be the probability that a migrant moves from birth town j to destination k, conditional on a randomly chosen migrant from j making the same move. Slight manipulation of the definition of the covariance of location decisions yields

$$C_{j,k} = P_{g,k}\left(\mu_{j,k} - P_{g,k}\right). \tag{2}$$

Equation (2) shows that variation in $C_{j,k}$ arises from two sources: the probability of moving to a destination, $P_{g,k}$, and the "marginal network effect," $\mu_{j,k} - P_{g,k}$. For example, $C_{j,k}$ could be large for a popular destination like New York because $P_{g,k}$ is large, even if $\mu_{j,k} - P_{g,k}$ is small. For less popular destinations, $\mu_{j,k} - P_{g,k}$ could be large, but $C_{j,k}$ will be small if $P_{g,k}$ is sufficiently small. Because $P_{g,k}$ varies tremendously in our setting, the covariance of location decisions or any aggregation of the covariance is not an attractive measure of the effect of networks.[15]

To measure the effect of birth town migration networks, we propose an intuitive network index that equals the expected increase in the number of people from birth town j that move to destination

[14]Proof:

$$\begin{aligned}
\beta_{j,k} &= \mathbb{E}[D_{i,j(i),k}D_{i',j(i'),k}|j(i) = j(i') = j] - \mathbb{E}[D_{i,j(i),k}D_{i',j(i'),k}|j(i) \neq j(i')] \\
&= \mathbb{E}[D_{i,j(i),k}D_{i',j(i'),k}|j(i) = j(i') = j] - (\mathbb{E}[D_{i,j,k}])^2 \\
&= \mathbb{C}[D_{i,j,k}, D_{i',j,k}] = C_{j,k}
\end{aligned}$$

The first line follows directly from equation (1). The second line follows from Assumptions 1 and 2. The third line follows from the definition of covariance.

[15]This issue applies in general when using the covariance of decisions to estimate the effects of social networks or social interactions. For example, there is considerable variation in the probability of working at specific locations or establishments.

county k when an arbitrarily chosen person i makes the same move,

$$\Delta_{j,k} \equiv \mathbb{E}[N_{-i,j,k}|D_{i,j,k}=1] - \mathbb{E}[N_{-i,j,k}|D_{i,j,k}=0], \tag{3}$$

where $N_{-i,j,k}$ is the number of people who move from j to k, excluding person i. A positive value of $\Delta_{j,k}$ indicates that the network increases the number of people who move from j to k, while $\Delta_{j,k}=0$ indicates no effect of the network.

The network index, $\Delta_{j,k}$, possesses several attractive properties. The network index permits meaningful comparisons, in intuitive units, of effects across heterogeneous receiving and sending locations. The network index also requires minimal assumptions about the specific behaviors that lead to network effects. For example, correlated location decisions could arise because individuals value living near their friends and family or because networks provide information about job opportunities. The network index also is consistent with and can be mapped directly to multiple structural models. For example, suppose that all migrants in town j form coalitions of size s, all members of a coalition move to the same destination, and all coalitions move independently of each other. In this case, the network index for each destination k depends only on the structural parameter s ($\Delta_{j,k} = s-1$), while the covariance of location decisions depends on the moving probability as well ($C_{j,k} = (s-1)P_{g,k}(1-P_{g,k})/(N_j-1)$). As another example, we connect the network index to a richer structural model in Section 5. The network index also can be estimated non-parametrically with increasingly available data.

In Appendix A, we show how to express the network index as

$$\Delta_{j,k} = \frac{(\mu_{j,k}-P_{g,k})(N_j-1)}{1-P_{g,k}} = \frac{C_{j,k}(N_j-1)}{P_{g,k}-P_{g,k}^2}. \tag{4}$$

Several features of equation (4) are noteworthy. First, the network index depends on the parameters governing social networks, $(P_{g,k}, C_{j,k})$. Second, the network index increases in the marginal network effect, $\mu_{j,k}-P_{g,k}$. If migrants move independently of each other, then $\mu_{j,k}-P_{g,k}=\Delta_{j,k}=0$. Finally, the network index does not necessarily increase in the number of migrants from birth town

j, N_j, as the marginal network effect might decrease in N_j.[16]

The network index captures actions that generate a positive correlation of location decisions among migrants from the same birth town, relative to what would be predicted by the decisions of migrants from nearby towns. While social networks might affect location decisions in other ways, the network index does not measure them. For example, if social networks affected whether individuals migrated, but not where they moved, then the network index would equal zero. Relatedly, the network index is an average over all migrants, so it could vary with the set of migrants if individuals differ in how much they influence and are influenced by others.[17]

The network index equals the expected increase in the number of people that move from j to k when a randomly chosen person makes the same move. This does not necessarily equal the expected increase in the number of people that move from j to k *because* a randomly chosen person makes the same move. The relationship between these two parameters depends on the underlying structural model. For example, in the coalition model described above – where all migrants in town j form coalitions of size s, all members of a coalition move to the same destination, and all coalitions move independently of each other – these two parameters are identical and equal to $s-1$. Alternatively, if each coalition has one leader, and all other members of the coalition follow the leader, then the network index equals $s-1$, but the expected increase in the number of people that move from j to k *because* a randomly chosen person makes the same move is $(s-1)/s$. This distinction arises because the network index relies on weak assumptions about the underlying structural model. The weakness of these assumptions, and the ability to map the network index directly to several structural models, are valuable features of our approach.

3.3 Estimating the Network Index

As suggested by equation (4), estimating the network index is straightforward. We first define birth town groups, and then non-parametrically estimate the underlying parameters $P_{g,k}$, $P^2_{g,k}$, and $C_{j,k}$.

[16] In addition, $-1 \leq \Delta_{j,k} \leq N_j - 1$. At the upper bound, all migrants from j move to the same location, while at the lower bound, migrants displace each other one-for-one.

[17] Our approach allows migration networks to influence out-migration, but we do not directly examine this channel.

We define birth town groups in two ways. Our preferred approach balances the inclusion of very close towns, for which Assumption 1 likely holds, with the inclusion of towns that are further away and lead to a more precise estimate of $P_{g,k}$. We divide each birth state into a grid of squares with sides x^* miles long and choose x^* separately for each state using leave-one-out cross validation. This technique is regularly used for bandwidth selection of matching estimators (e.g., Black and Smith, 2004), and it chooses the grid size that minimizes the mean squared error of the observed migration propensities and "out-of-sample" forecasts from other towns in the same birth town group.[18] Given x^*, the location of the grid is determined by a single latitude-longitude reference point. Network index estimates are very similar across four different reference points, so we average estimates across them.[19]

An alternative definition of a birth town group is a county. If the value of choosing a destination varied sharply across county borders in the sending region, then this definition would be appropriate. However, differences across counties, such as local government policies and elected officials, do not necessarily imply that counties are better birth town groups, as what matters is whether these differences affect the ex-ante probability of choosing a destination, conditional on migrating. An advantage of cross-validation is that it facilitates comparisons across birth states, which differ in average county size. We emphasize results based on cross validation in the main text and include results based on counties in the appendix.[20]

We estimate the probability of moving from birth town group g to destination county k as the

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[18]That is,

$$x^* = \arg\min_x \sum_j \sum_k \left(N_{j,k}/N_j - \hat{P}_{g(x),-j,k} \right)^2,$$

where $\hat{P}_{g(x),-j,k} = \sum_{j' \neq j \in g(x)} N_{j',k} / \sum_{j' \neq j \in g(x)} N_{j'}$ is the average moving propensity from the birth town group of size x, excluding moves from town j. If there is only one town within a group g, then we define $\hat{P}_{g(x),-j,k}$ to be the statewide moving propensity. We search over even integers for convenience. Appendix Table A.2 reports the values of x^* chosen by cross-validation.

[19]To construct reference points, we use the mean latitude in a state and the mean latitude plus one-third of x^*, scaled in appropriate units. We use analogous reference points for longitude.

[20]Appendix Figures A.3 and A.4 describe the number of birth towns per group when groups are defined using cross validation for Southern black and Great Plains white migrants. The median number of towns per group is 15 for African Americans and 39 for whites from the Great Plains. Appendix Figures A.5 and A.6 describe the number of towns per county. All groups used in estimation have at least two towns, because we cannot estimate $C_{j,k}$ or $P^2_{g,k}$ without multiple towns in the same group.

total number of people who move from g to k divided by the total number of migrants in g,

$$\widehat{P_{g,k}} = \frac{\sum_{j\in g} N_{j,k}}{\sum_{j\in g} N_j}. \tag{5}$$

We estimate the squared moving probability and covariance of location decisions using the closed-form solution implied by equation (1),[21]

$$\widehat{P^2_{g,k}} = \frac{\sum_{j\in g}\sum_{j'\neq j\in g} N_{j,k}N_{j',k}}{\sum_{j\in g}\sum_{j'\neq j\in g} N_j N_{j'}} \tag{6}$$

$$\widehat{C_{j,k}} = \frac{N_{j,k}(N_{j,k}-1)}{N_j(N_j-1)} - \widehat{P^2_{g,k}}. \tag{7}$$

The final component of the network index is the number of migrants from birth town j, N_j.

Given $(\widehat{P_{g,k}}, \widehat{P^2_{g,k}}, \widehat{C_{j,k}}, N_j)$, we can estimate the network index, $\Delta_{j,k}$, using equation (4). However, each estimate $\widehat{\Delta_{j,k}}$ depends largely on a single birth town observation. To conduct inference, increase the reliability of our estimates, and decrease the number of parameters reported, we aggregate network index estimates across all birth towns in each state,

$$\widehat{\Delta_k} = \sum_j \left(\frac{\widehat{P_{g(j),k}} - \widehat{P^2_{g(j),k}}}{\sum_{j'} \widehat{P_{g(j'),k}} - \widehat{P^2_{g(j'),k}}} \right) \widehat{\Delta_{j,k}}, \tag{8}$$

where $g(j)$ is the group of town j. The weights in equation (8) minimize the variance of $\widehat{\Delta_k}$ under the assumption that $\Delta_{j,k}$ does not vary across birth towns within a state.[22] The destination-level network index estimate, $\widehat{\Delta_k}$, is robust to small estimates of $P_{g,k}$, which can blow up estimates of $\Delta_{j,k}$. We also construct birth county-level network index estimates by aggregating across destina-

[21] Equation (6) yields an unbiased estimate of $P^2_{g,k}$ under Assumptions 1 and 2. In contrast, simply squaring $\widehat{P_{g,k}}$ would result in a biased estimate.

[22] See Appendix B for details.

tions and towns within birth county c,

$$\widehat{\Delta_c} = \sum_k \sum_{j \in c} \left(\frac{\widehat{P_{g(j),k}} - \widehat{P^2_{g(j),k}}}{\sum_{k'} \sum_{j' \in c} \widehat{P_{g(j'),k'}} - \widehat{P^2_{g(j'),k'}}} \right) \widehat{\Delta_{j,k}}. \tag{9}$$

Birth county-level network index estimates have similar conceptual and statistical properties as destination-level network index estimates.

To facilitate exposition, we have described estimation of the network index in terms of four distinct components, $(\widehat{P_{g,k}}, \widehat{P^2_{g,k}}, \widehat{C_{j,k}}, N_j)$. However, network index estimates depend only on observed population flows, and equation (8) forms the basis of an exactly identified generalized method of moments (GMM) estimator. To estimate the variance of $\widehat{\Delta_k}$, we treat the birth town group as the unit of observation and use a GMM variance estimator. This is akin to calculating heteroskedastic robust standard errors clustered by birth town group.[23] Appendix B contains details.

3.4 An Extension to Assess the Validity of Our Empirical Strategy

The key threat to our empirical strategy is that the ex-ante value of moving to a destination differs across nearby birth towns in the same group. If, contrary to this threat, Assumption 1 were true, then geographic proximity would adequately control for the relevant determinants of location decisions, and using birth town covariates to explain moving probabilities would not affect network index estimates.

We assess this threat by allowing moving probabilities to depend on birth town covariates,

$$P_{j,k} = \rho_{g,k} + X_j \pi_k, \tag{10}$$

where $\rho_{g,k}$ is a birth town group-destination fixed effect, and X_j is a vector of birth town covariates whose effect on the moving probability can differ across destinations. In X_j we include an indi-

[23]Treating birth town groups as the units of observation has no impact on the point estimate, $\widehat{\Delta_k}$. We estimate clustered standard errors because the estimates $\widehat{P_{g,k}}$ and $\widehat{P^2_{g,k}}$ are common to all birth towns within g.

cator for being along a railroad, an indicator for having above-median black population share, and four indicators corresponding to population quintiles.[24] These covariates, available from the Duke SSA/Medicare data and the railroad information used in Black et al. (2015), capture potentially relevant determinants of location decisions. For example, migrants born in larger towns might have more human capital or information, and these resources might make certain destinations more attractive, causing our network index estimates to reflect variables correlated with birth town size instead of migration networks.

To implement this extension, we construct an alternative network index estimate using an alternative moving probability estimate, $\widetilde{P_{j,k}}$, equal to the fitted value from the OLS regression

$$\frac{N_{j,k}}{N_j} = \rho_{g,k} + X_j \pi_k + e_{j,k}. \tag{11}$$

We use fitted values from a separate OLS regression, implied by equation (10), to form an alternative squared moving probability estimate, $\widetilde{P^2_{j,k}}$.[25] We estimate all equations separately for each birth state. Similarity between the baseline and alternative network index estimates would provide support for our empirical strategy.[26]

[24]We construct percentiles for black population share and population separately for each birth state.

[25]We estimate $\widetilde{P^2_{j,k}}$ using fitted values from the OLS regression

$$\frac{N_{j,k}}{N_j}\frac{N_{j',k}}{N_{j'}} = \rho_{g(j),k}\rho_{g(j'),k} + X_j\pi_k\rho_{g(j'),k} + X_{j'}\pi_k\rho_{g(j),k} + (X_j\pi_k)(X_{j'}\pi_k) + e'_{j,j',k}$$

for different birth towns, $j \neq j'$.

[26]When estimating the variance of our network index estimates under this extension, we ignore the variance that arises because $\widetilde{P_{j,k}}$ and $\widetilde{P^2_{j,k}}$ rely on OLS estimates. Accounting for this variance would make our estimates with and without covariates appear even more similar when performing statistical tests. An alternative way of assessing the validity of Assumption 1 is testing whether the parameter vector $\pi_k = 0$ in equation (11). We prefer to test the difference in network index estimates because this approach allows us to consider the statistical and substantive significance of any differences.

4 Results: The Effects of Migration Networks on Location Decisions

4.1 Network Index Estimates

Table 1 provides an overview of the long-run population flows that we use to estimate the effects of migration networks. Our data contain 1.3 million African Americans born in the South from 1916-1936, 1.9 million whites born in the Great Plains, and 2.6 million whites born in the South. In old age, 42 percent of African Americans born in the South and 35 percent of whites born in the Great Plains lived outside their birth region, while only nine percent of whites born in the South lived elsewhere.[27] We focus on Southern-born African Americans and Great Plains-born whites, and leave results for Southern-born whites for the appendix. On average, there were 142 Southern black migrants and 181 Great Plains white migrants per birth town (Appendix Table A.3).

We begin with some examples that illustrate how we identify the effects of birth town migration networks. Table 2 shows the birth town to destination county migration flows that would be most unlikely in the absence of such networks. Panel A shows that 10-50 percent of African American migrants from these birth towns lived in the same destination county in old age, far exceeding the 0.1-1.6 percent of migrants from each birth state that lived in the same county. The observed moving propensities are 49-65 standard deviations larger than what would be expected if migrants moved independently of each other according to the statewide moving propensities. The estimated moving probabilities, $\widehat{P_{g,k}}$, exceed the statewide moving propensities, suggesting a meaningful role for local conditions in location decisions. Most importantly, the observed moving propensities are much larger than the estimated moving probabilities, consistent with positive covariance and network index estimates. The results in Panel B for Great Plains whites are similar.

To summarize the effects of migration networks for all location decisions in our data, Table 3 reports averages of destination-level network index estimates, $\widehat{\Delta_k}$. For African Americans, unweighted averages vary from 0.46 (Louisiana) to 0.90 (Mississippi). Averages weighted by the number of migrants in each destination vary from 0.81 (Florida) to 2.62 (South Carolina) and are

[27]Census data show that return migration was quite low among Southern-born African Americans and much higher among Southern-born whites (Gregory, 2005).

larger because migration networks have stronger effects in destinations with more migrants. We prefer the weighted average as a summary measure because it better reflects the experience of a randomly chosen migrant and depends less on our decision to combine destination counties with fewer than 10 migrants. Across all states, the migrant-weighted average of destination-level network index estimates is 1.94; this means that when one randomly chosen African American moves from a birth town to a destination county, then 1.94 additional black migrants from the same birth town make the same move on average. Panel B contains results for white moves out of the Great Plains. The weighted average for whites is 0.38, only one-fifth the size of the black average.[28] African American migrants relied on birth town migration networks more heavily in making their long-run location decisions.

We provide a more complete picture in Figure 3, which plots the distribution of destination-level network index estimates.[29] Across the board, network index estimates for African Americans are larger than those for whites. Migration networks have particularly strong effects for some destinations, especially for black migrants, and relatively weak effects for most destinations. Below, we examine whether destinations' economic characteristics can explain this heterogeneity.

To examine the effects of migration networks even more closely, Figure 4 plots the spatial distribution of destination-level network index estimates for Mississippi-born African Americans. We estimate strong network effects for several destinations: 23 counties have a network index estimate greater than 3, and 58 counties have a network index estimate between 1 and 3. These counties lie in the Midwest and, to a lesser degree, the Northeast. The figure also shows that African Americans moved to a relatively small number of destination counties, consistent with limited opportunities, information, or interest in moving to many places in the U.S.[30] We estimate

[28]Appendix Table A.4 shows that results are similar when we define birth town groups using counties. For Southern black migrants, the linear (rank) correlation between the destination-level network index estimates using cross validation and counties is 0.858 (0.904). For whites from the Great Plains, the linear (rank) correlation is 0.965 (0.891). Appendix Table A.5 shows that average network index estimates for Southern whites are somewhat smaller than for whites from the Great Plains.

[29]Appendix Figure A.7 displays the associated t-statistic distributions, and Appendix Figures A.8 and A.9 display analogous results for whites from the South. A destination county can appear multiple times in these figures because we estimate destination-level network indices separately for each birth state.

[30]In Figure 4, the counties in white received less than 10 migrants.

a strong network effect ($\widehat{\Delta_k} > 3$) in Rock County, Wisconsin, consistent with historical accounts of African Americans who moved from Mississippi to Beloit, which is located there (Bell, 1933; Rubin, 1960; Wilkerson, 2010).

Figure 5 maps the destination-level network index estimates for whites from North Dakota. We find little evidence of strong network effects, although one exception is San Joaquin county ($\widehat{\Delta}_k > 3$), an area described memorably in *The Grapes of Wrath* (Steinbeck, 1939).[31] Unlike black migrants, whites moved to a large number of destinations throughout the U.S. The difference between the number of destinations chosen by Mississippi black and North Dakota white migrants is striking, especially because our data contain almost 30,000 more migrants from Mississippi. While factors, like discrimination, that led African Americans to move to a smaller number of destinations could also explain their greater reliance on migration networks, the limited number of destinations chosen by African Americans does not mechanically generate stronger network effects, because we identify these effects using the location choices of nearby migrants.[32] Appendix Figures A.10 and A.11, for South Carolina-born black and Kansas-born white migrants, show similar patterns.

4.2 Support for Empirical Strategy, Additional Results, and Robustness

To assess the validity of our empirical strategy, we examine whether network index estimates change when using birth town covariates to explain moving probabilities, as discussed in Section 3.4. Table 4 reports weighted averages of destination-level network index estimates with and without covariates. There are no substantively or statistically significant differences between the two sets of estimates when we examine birth states individually. When pooling all Southern states together, the estimates are very similar in magnitude (1.94 and 1.92) and statistically indistinguishable ($p = 0.76$). When pooling all Great Plains states together, the estimates again are very similar in magnitude (0.38 and 0.36), but are statistically distinguishable ($p = 0.02$). The destination-level

[31] In *The Grapes of Wrath*, the Joad family travels from Oklahoma to the San Joaquin Valley. Gregory (1989) notes that the (fictional) Joads were poorer than many migrants from the Great Plains.

[32] Factors that limit the destinations chosen by a group, like discrimination, will tend to increase the probability of moving to a destination, but as discussed above, a higher moving probability does not mechanically increase the network index.

network index estimates with and without covariates also are highly correlated: the linear (rank) correlation is 0.914 (0.992) for African Americans from the South and 0.939 (0.988) for whites from the Great Plains. On net, we view this evidence as indicating that geographic proximity adequately controls for the relevant determinants of location decisions, supporting the validity of our empirical strategy.

Table 5 shows that our results are not driven by migration from the largest birth towns or migration to the largest destinations and, relatedly, that there is limited heterogeneity in network index estimates on these dimensions. Birth town size could be correlated with unobserved determinants of migration networks, such as the level of social and human capital or information about destinations. Still, it is not clear beforehand whether networks will vary with the size of receiving or sending locations. For reference, column 1 of Table 5 reports weighted averages of destination-level network index estimates when including all birth towns and destinations. In column 2, we exclude birth towns with at least 20,000 residents in 1920 when estimating each destination-level network index.[33] Column 3 excludes destination counties that intersect with the ten largest non-Southern consolidated metropolitan statistical areas (CMSAs) as of 1950, in addition to counties that received less than 10 migrants.[34] We exclude both large birth towns and large destinations in column 4. The average network index estimates are similar across all four specifications for both Southern African Americans and Great Plains whites.[35]

To further understand the nature of migration networks, we examine whether the location decisions of black migrants influenced white migrants from the same Southern birth town, and vice versa. While African Americans and whites could have shared information about opportunities in the North, segregation in the Jim Crow South makes cross-race interactions unlikely. Appendix C

[33]The excluded birth towns are Birmingham, Mobile, and Montgomery, Alabama; Jacksonville, Miami, Pensacola, and Tampa, Florida; Atlanta, Augusta, Columbus, Macon, and Savannah, Georgia; Baton Rouge, New Orleans, and Shreveport, Louisiana; Jackson and Meridian, Mississippi; Asheville, Charlotte, Durham, Raleigh, Wilmington, and Winston-Salem, North Carolina; Charleston, Greenville, and Spartanburg, South Carolina; Hutchinson, Kansas City, Topeka, and Wichita, Kansas; Lincoln and Omaha, Nebraska; Fargo, North Dakota; Muskogee, Oklahoma City, and Tulsa, Oklahoma; and Sioux Falls, South Dakota

[34]The ten CMSAs are New York, Chicago, Los Angeles, Philadelphia, Boston, Detroit, Washington, D.C., San Francisco, Pittsburgh, and St. Louis. The first nine of these are also the largest non-Great Plains (and border region) CMSAs.

[35]Appendix Table A.6 reports similar results for Southern-born whites.

describes how we estimate the effects of cross-race migration networks, and Appendix Table A.7 displays little evidence of such effects. In addition, there is little correlation between destination-level network index estimates for African Americans and whites from the South: the linear (rank) correlation is 0.076 (0.149). This also implies that our network index estimates do not simply reflect unobserved characteristics of certain Southern towns.

Appendix Table A.8 displays results where, instead of choosing the grid size by cross validation, we use grid sizes of 50, 100, and 200 miles. Network estimates increase somewhat with the grid size.[36] Most importantly, network index estimates for African Americans exceed those of whites from the Great Plains by a similar magnitude for all grid sizes. This implies that our results are not driven by whites having more dispersed migration networks.

While the Duke SSA/Medicare data include most individuals born from 1916-1936, coverage rates are not perfect. Appendix D discusses the consequences of this measurement error in detail. We believe that imperfect coverage most likely leads us to understate the importance of migration networks.

4.3 The Role of Family Migration

The network index might capture the effect of family members from the same birth town on migrants' location decisions. While family migration is not a threat to our empirical strategy, it would be interesting to know the extent to which migration networks reflect within-family connections. Unfortunately, we do not observe family relationships and so cannot study this question directly. However, we can examine whether our results stem entirely from the migration of male-female couples. If this were true, we would estimate negligible network indices when using male-only or female-only samples. Appendix Table A.10 shows that network index estimates are similar in magnitude among men and women, implying that our results do not simply reflect the migration of couples.[37] Our sample likely contains very few sets of parents and children, since we only include

[36]This could arise because violations of Assumption 1 are more likely or violations of Assumption 2 are less consequential with larger birth town groups. Given the tradeoffs, we prefer to choose the grid size using cross validation.

[37]The similarity between men and women is not surprising given the relative sex balance among migrants in this period (Gregory, 2005). The sizable effects among women only also indicate that our results are not driven by in-

individuals born from 1916-1936.

A related question is whether differences in family size explain the black-white network effect gap. As a first step, we use the 1940 Census to measure the average within-household family size for individuals born from 1916-1936. African Americans from the South had families that were 17 percent larger than whites from the Great Plains (6.16 versus 5.25). This difference is too small to explain our finding that average network index estimates are 410 percent larger among African Americans. To construct an upper bound on extended family size, we use the 100 percent sample of the 1940 Census to count the average number of individuals in a county born from 1916-1936 with the same last name (Minnesota Population Center and Ancestry.com, 2013). We find that Southern black family networks likely were no more than 270 percent larger than those for Great Plains whites (54.5 versus 14.7). This upper bound is sizable, but still less than the 410 percent difference in network effects. Appendix E contains a more formal discussion. We conclude that differences in family size might explain some, but not all, of the difference in network effects between black and white migrants.[38]

4.4 Migration Networks and Economic Characteristics of Receiving and Sending Locations

To better understand why birth town migration networks affected location decisions, we relate network index estimates to economic characteristics of receiving and sending locations.

We first consider the characteristics of receiving locations. Employment opportunities were one of the most important considerations, and relatively high wages made manufacturing jobs particularly attractive. In the presence of imperfect information among migrants about employment opportunities, networks might have directed their members to destinations with more manufacturing employment. This is the story of John McCord, told in Section 2. Because individuals living in the South and Great Plains had more information about the largest destinations, the imperfect information channel suggests a stronger relationship between network effects and manufacturing

dividuals serving together during World War II. Further evidence of this comes from the similarity of the results for individuals born from 1916-1925 and 1926-1936 (Appendix Table A.10).

[38]Conditional on family size, black and white migrants could have differed in the extent to which they tended to follow other family members. We do not have data that let us examine this possibility.

employment intensity in smaller destinations. In contrast, if information about employment opportunities was widespread, then network effects might not be stronger in destinations with more manufacturing. Similar patterns could arise if workers relied on their networks for job referrals.[39] Destinations with more agriculture employment also might have been attractive because migrants had experience in this sector. Pecuniary moving costs, which were largely determined by distance and railroads, represented another key consideration. Lower moving costs could have fostered networks by facilitating the transmission of information. On the other hand, migrants might have been willing to pay high moving costs only if they received information or benefits from a network.

To explore these hypotheses, we regress destination-level network index estimates on county covariates. Column 1 of Table 6 shows that network effects among African Americans are larger in destinations with a higher 1910 manufacturing employment share: a one standard deviation increase is associated with an increase in the network index of 0.22 people.[40] Column 2 shows that the positive relationship between manufacturing employment and network effects is almost seven times larger in smaller destinations.[41] There is little relationship between network effects and the agriculture employment share. We also find stronger network effects in destinations that were closer to and could be reached by rail directly or with one stop from migrants' birth state. Network effects are stronger in destinations with a smaller black population share in 1900, suggesting that networks helped migrants find opportunities in new places. One possible concern is that these results do not reflect characteristics of destination counties, but instead characteristics of birth states linked to destinations via vertical migration patterns. Column 3 indicates that this concern is unimportant, as adding birth state fixed effects has very little impact. Columns 4-6 present results for white migrants from the Great Plains. For this group, there is little relationship between

[39]There is a large literature on social networks and employment opportunities. Recent examples include Topa (2001); Munshi (2003); Ioannides and Loury (2004); Bayer, Ross and Topa (2008); Hellerstein, McInerney and Neumark (2011); Beaman (2012); Burks et al. (2015); Schmutte (2015); Heath (2016).

[40]Appendix Table A.11 contains summary statistics. Appendix Figure A.12 plots the bivariate relationship between network index estimates and 1910 manufacturing employment share, showing the considerable variation in manufacturing employment share across destinations.

[41]Small destination counties are those that do not intersect with the ten largest non-South CMSAs in 1950 (New York, Chicago, Los Angeles, Philadelphia, Boston, Detroit, Washington, D.C., San Francisco, Pittsburgh, and St. Louis).

network effects and the share of employment in manufacturing or agriculture.[42] Network effects are again stronger in destinations that could be reached more easily by rail, but slightly weaker in destinations that were closer.[43]

Overall, the results in Table 6 suggest that black migration networks responded more to attractive employment opportunities, especially in smaller destinations, and moving costs. This is consistent with black migrants relying more heavily on their networks for information about employment opportunities or job referrals, possibly because they faced greater discrimination in labor markets or had fewer resources.

We next consider the relationship between migration networks and characteristics of sending counties. Networks could have been particularly valuable in locating jobs or housing for migrants from poorer communities who had fewer resources to engage in costly search (McKenzie and Rapoport, 2007). Alternatively, resources that facilitated migration might have been a prerequisite for networks to influence location decisions. Another potentially important characteristic is population density, which could have strengthened networks through frequent interactions (Chay and Munshi, 2015). We also consider literacy rates and, for African Americans, access to Rosenwald schools, which improved educational attainment in this period (Aaronson and Mazumder, 2011). The relationship between education and network effects is theoretically ambiguous, as education could promote social ties while also increasing the relative return to choosing a non-network destination. In addition, we examine whether networks were stronger in counties with greater access to railroads, which could have facilitated the transmission of information through both network and non-network channels.

Table 7 displays results from regressing birth county-level network index estimates on county characteristics. Columns 1 and 2 contain results for black moves out of the South. Network effects were stronger in counties with higher black farm ownership rates (which we use to proxy for assets), black population density, and black literacy rates. However, these estimates are relatively

[42]For destinations that intersect with the largest CMSAs, networks are actually weaker in destinations with more manufacturing.

[43]Results are qualitatively similar when using counties to define birth town groups (Appendix Table A.12). Results for Southern whites are in Appendix Table A.13.

imprecise, and only the coefficient on the literacy rate is significant at the five percent level.[44] Results are similar in column 2, where we include birth state fixed effects to address the possibility that our results are driven by destination factors, such as labor demand, that are linked to certain areas of the South through vertical migration patterns. The estimates in column 2 imply that a one standard deviation increase in log black density is associated with a 1.08 person increase in the network index, and a one standard deviation increase in the black literacy rate is associated with a 0.48 person increase.[45] We find little evidence that network effects varied with railroad access, although the standard errors are fairly large.

Columns 3 and 4 present results for white moves out of the Great Plains, where we use the white farm ownership rate, white population density, and white literacy rate as explanatory variables.[46] Overall, white network effects appear to be less sensitive to birth county characteristics. The notable exception is that white network effects are stronger in birth counties with lower literacy rates. This differs from African Americans, for whom network effects are stronger in birth counties with higher literacy rates. One possible explanation is that only whites with relatively little human capital relied on their social networks to obtain employment, while African Americans with higher human capital relied on their networks to overcome the more severe discrimination they faced.

5 A Structural Model of Migration Networks and Location Decisions

As discussed above, the network index is consistent with and can be mapped to multiple structural models. In this section, we map the network index to one such model, in which migration networks arise because some migrants follow other migrants to a destination. Our model shares this basic structure with Glaeser, Sacerdote and Scheinkman (1996), but we extend previous work by modeling the interdependence between various destinations, as is necessary in a multinomial choice

[44] The positive correlation between network effects and literacy rates is unlikely to be driven by black migrants reading the same newspaper, as only newspapers from the largest destinations (such as Chicago) circulated in the South.

[45] Appendix Table A.14 contains summary statistics for birth county characteristics.

[46] We do not include Rosenwald school exposure in columns 3 or 4 because Rosenwald schools existed primarily in the South.

problem, and allowing for more than two types of agents. The additional structure in the model allows us to examine counterfactual location decisions in the absence of migration networks.

5.1 Model

Migrants from birth town j are indexed on a circle by $i \in \{1, \dots, N_j\}$, where N_j is the total number of migrants from j. For migrant i, destination k belongs to one of three preference groups: high (H_i), medium (M_i), or low (L_i). The high preference group contains a single destination. In the absence of migration networks, the destination in H_i is most preferred, and destinations in M_i are preferred over those in L_i.[47] A migrant never moves to a destination in L_i. A migrant chooses a destination in M_i if and only if their neighbor, $i-1$, chooses the same destination. A migrant chooses a destination in H_i if their neighbor chooses the same destination or their neighbor selects a destination in L_i.

Migrants from the same birth town differ in their preferences over destinations. The probability that destination k is in the high preference group for a migrant from town j is $h_{j,k} \equiv \mathbb{P}[k \in H_i | i \in j]$, and the probability that destination k is in the medium preference group is $m_{j,k} \equiv \mathbb{P}[k \in M_i | i \in j]$. These probabilities arise from expected utility maximization problems solved by migrants. We do not need to specify migrants' utility functions, but expected wages and transportation costs are among the relevant factors. We also do not need to specify why some migrants choose the same destination as their neighbor. For example, neighbors might provide information about employment opportunities, or migrants might value living near friends and family.

The probability that a randomly chosen migrant i moves from j to k is

$$P_{j,k} \equiv \mathbb{P}[D_{i,j,k} = 1] = \mathbb{P}[D_{i-1,j,k} = 1, k \in H_i] + \mathbb{P}[D_{i-1,j,k} = 1, k \in M_i] + \sum_{k' \neq k} \mathbb{P}[D_{i-1,j,k'} = 1, k \in H_i, k' \in L_i]. \quad (12)$$

[47] The assumption that H_i is a non-empty singleton ensures that migrant i has a well-defined location decision in the absence of networks. We could allow H_i to contain many destinations and specify a decision rule among the elements of H_i. This extension would complicate the model without adding any new insights.

The first term on the right hand side of equation (12) is the probability that a migrant's neighbor moves to k, and k is in the migrant's high preference group; in this case, the neighbor's decision reinforces the migrant's desire to move to k. The second term is the probability that a migrant moves to k only because their neighbor moved there. The third term is the probability that a migrant moves to k because it is in the high preference group and the neighbor's chosen destination is in the low preference group. Using the parameters defined above, we rewrite equation (12) as

$$P_{j,k} = P_{j,k}h_{j,k} + P_{j,k}m_{j,k} + \sum_{k' \neq k} P_{j,k'}h_{j,k}\left(\frac{1-h_{j,k'}-m_{j,k'}}{1-h_{j,k'}}\right). \tag{13}$$

The share of migrants from birth town j living in destination k that chose their destination because of the network equals $m_{j,k}$.[48] Hence, the number of migrants that chose destination k because of the network is $N_k^{\text{network}} \equiv \sum_j N_{j,k}m_{j,k}$, where $N_{j,k}$ is the number of migrants that moved from j to k. In the absence of networks, where $m_{j,k} = 0$, migrants move to the destination in H_i. As a result, in the counterfactual in which networks do not influence location decisions, the probability of moving from j to k is $h_{j,k}$, and the number of migrants in destination k is $N_k^{\text{cf}} \equiv \sum_j N_j h_{j,k}$. Our goal is to estimate both $m_{j,k}$ and $h_{j,k}$.

5.2 Estimation

To facilitate estimation, we introduce an auxiliary parameter. The probability that destination k is in the medium preference group, conditional on not being in the high preference group, is $\nu_{j,k} \equiv \mathbb{P}[k \in M_i | k \notin H_i, i \in j]$. The conditional probability definition for $\nu_{j,k}$ implies that

[48] The share of migrants from birth town j living in destination k that chose their destination because of the network is $\mathbb{P}[k \in M_i | D_{i,j,k} = 1]$. By Bayes' theorem, this equals

$$\mathbb{P}[k \in M_i | D_{i,j,k} = 1] = \frac{\mathbb{P}[D_{i,j,k} = 1 | k \in M_i]\,\mathbb{P}[k \in M_i]}{\mathbb{P}[D_{i,j,k} = 1]} = \frac{P_{j,k}m_{j,k}}{P_{j,k}} = m_{j,k}$$

because $\mathbb{P}[D_{i,j,k} = 1 | k \in M_i] = \mathbb{P}[D_{i-1,j,k} = 1] = P_{j,k}$.

$\nu_{j,k} = m_{j,k}/(1 - h_{j,k})$. Using $\nu_{j,k}$ allows us to simplify equation (13) to

$$P_{j,k} = P_{j,k}\nu_{j,k} + \sum_{k'=1}^{K} P_{j,k'}(1 - \nu_{j,k'})h_{j,k}. \tag{14}$$

We next connect the structural model to the network index. The model implies that the average covariance of location decisions, $C_{j,k}$, equals

$$C_{j,k} = \frac{2P_{j,k}(1 - P_{j,k}) \sum_{a=1}^{N_j-1}(N_j - a) \left(\frac{\rho_{j,k} - P_{j,k}}{1 - P_{j,k}}\right)^a}{N_j(N_j - 1)}, \tag{15}$$

where $\rho_{j,k} \equiv \mathbb{P}[D_{i,j,k} = 1 | D_{i-1,j,k} = 1, i \in j] = h_{j,k} + m_{j,k}$ is the probability that migrant i moves to destination k given that their neighbor moves there.[49]

We continue to maintain Assumption 1, so that the probability of moving from j to k is the same for all birth towns in the same birth town group g. In the structural model, Assumption 1 holds because we assume that $m_{j,k}$ and $h_{j,k}$ are equal for all birth towns in the same group. This implies that $\rho_{j,k}$ is also constant across birth towns in the same group. The justification for this assumption is the same as previously discussed.

Imposing this assumption, substituting equation (15) into the expression for the network index in equation (4), simplifying, and taking the limit as $N_j \to \infty$ yields

$$\Delta_{g,k} = \frac{2(\rho_{g,k} - P_{g,k})}{1 - \rho_{g,k}}, \tag{16}$$

where $\Delta_{g,k}$ is the birth town group-destination network index that forms the basis of our estimation, as described above. Equation (16) can be rearranged to show that

$$\rho_{g,k} = \frac{2P_{g,k} + \Delta_{g,k}}{2 + \Delta_{g,k}}. \tag{17}$$

[49]Equation (15) follows from the fact that the covariance of location decisions for individuals i and $i + n$ is $\mathbb{C}[D_{i,j,k}, D_{i+n,j,k}] = P_{j,k}(1 - P_{j,k}) \left(\frac{\rho_{j,k} - P_{j,k}}{1 - P_{j,k}}\right)^n$.

We use equation (17) to estimate $\rho_{g,k}$ with our estimates of $P_{g,k}$ and $\Delta_{g,k}$.

Equation (14), plus the facts that $\nu_{g,k} = m_{g,k}/(1 - h_{g,k})$ and $\rho_{g,k} = h_{g,k} + m_{g,k}$, imply that

$$\rho_{g,k} = \nu_{g,k} + \frac{P_{g,k}(1 - \nu_{g,k})^2}{\sum_{k'=1}^{K} P_{g,k'}(1 - \nu_{g,k'})}. \tag{18}$$

We use equation (18) to estimate $\nu_g \equiv (\nu_{g,1}, \ldots, \nu_{g,K})$ using our estimates of $(P_{g,1}, \ldots, P_{g,K}, \rho_{g,1}, \ldots, \rho_{g,K})$. We employ a computationally efficient algorithm that leverages the fact that equation (18) is a quadratic in $\nu_{g,k}$, conditional on $\sum_{k'=1}^{K} P_{g,k'}(1 - \nu_{g,k'})$. We initially assume that $\sum_{k'=1}^{K} P_{g,k'}(1 - \nu_{g,k'}) = \sum_{k'=1}^{K} P_{g,k'} = 1$, then solve for $\nu_{g,k}$ using the quadratic formula, then construct an updated estimate of $\sum_{k'=1}^{K} P_{g,k'}(1 - \nu_{g,k'})$, and then solve again for $\nu_{g,k}$ using the quadratic formula. We require that each estimate of $\nu_{g,k}$ lies in $[0, 1]$. This iterated algorithm converges very rapidly in essentially all cases.[50] Finally, we use equation (14) to estimate $h_{g,k}$ with our estimates of $\rho_{g,k}$ and $\nu_{g,k}$, and we estimate $m_{g,k}$ using the fact that $m_{g,k} = \rho_{g,k} - h_{g,k}$.

The parameters of the structural model are exactly identified. We jointly identify $m_{j,k}$ and $h_{j,k}$ from estimates of moving probabilities and network indices. Estimates of $m_{j,k}$ tend to reflect the network index: if $m_{j,k} = 0$, then equation (13) implies that $P_{j,k} = h_{j,k}$ and equation (16) implies that $\Delta_{j,k} = 0$. Location decisions differ across nearby towns due to exogenous shifters in the location decisions of some migrants. For example, if a migrant moves to destination k for some idiosyncratic reason, then other migrants will tend to follow. This captures the story of John McCord, described in Section 2.

5.3 Results

Table 8 reports estimates of the percent of migrants that chose their destination because of migration networks, calculated as migrant-weighted averages of $100 \times (\widehat{N_k^{\text{network}}}/N_k)$. On average,

[50]The algorithm converges in all cases for Great Plains white migrants. For Southern black migrants, there are three birth town groups for which the algorithm does not converge because our estimates of $P_{g,k}$ and $\rho_{g,k}$ do not yield a real solution to the quadratic formula. We set $\hat{\nu}_{g,k}$ equal to zero for any (g, k) observation for which the quadratic formula solution does not exist. The motivation for this is that our estimates of $P_{g,k}$ and $\rho_{g,k}$ in these cases are consistent with negative values of $\nu_{g,k}$, even though this is not a feasible solution. Our results are nearly identical when dropping these cases, which is not surprising because these three birth town groups account for a negligible share of the 223 groups used in our estimation for Southern black migrants.

we estimate that 34 percent of Southern black migrants chose their long-run location because of their birth town migration network. There is considerable variation across destination regions. For example, of Mississippi-born migrants, 17 percent of Northeast-bound, 40 percent of Midwest-bound, and 23 percent of West-bound migrants chose their location because of their migration network.[51] On average, 13 percent of Great Plains white migrants chose their long-run location because of their migration network.

Table 9 illustrates the effects of migration networks for selected destinations. We report the actual number of migrants and the number of migrants in a counterfactual without migration networks, for counties with the largest increases and decreases in migration. In the absence of migration networks, we estimate that Cook County, Illinois (home of Chicago) would experience a 29 percent decline in Southern black migrants. Los Angeles, Detroit, Philadelphia, and Baltimore also would have considerably fewer migrants, experiencing declines from 11 to 25 percent. The largest increases in migration would be to Queens, New York; Prince George's County, Maryland (near Washington); and Oakland County, Michigan (near Detroit). In the absence of migration networks, there would be considerably fewer Great Plains white migrants in several California counties: those containing Los Angeles, Bakersfield, Fresno, and Stockton would experience declines of 20 to 28 percent. These results show that migration networks account for a sizable portion of the migration to prominent destinations, and consequently that migration networks had important effects on the distribution of population across the U.S.[52]

Since migration networks clearly affected where individuals moved, a natural question is whether these networks led migrants to live in areas with worse economic opportunities, as could happen if networks limited later migratory responses to economic shocks. To study this, we examine how characteristics of migrants' location would change in a counterfactual without migration networks.[53] In Table 10, column 1 of Panel A shows that the average Southern black migrant lived

[51] This regional variation is also apparent in estimates of the network index (Appendix Tables A.16 and A.17).

[52] Appendix Table A.18 reports counterfactual migration flows from birth state to destination region in the absence of migration networks. The results show that migration networks were important determinants of vertical migration patterns, one of the most widely known features of the Great Migration.

[53] A different question, which we do not answer, is whether migration networks had a causal effect on migrants' labor market outcomes.

in a county where the unemployment rate was 7.5 percent in 2000. In the no-network counterfactual, this falls to 7.3 percent. Hence, for the 34.5 percent of migrants that would move in the counterfactual, the mean unemployment rate falls by 0.7 percentage points. The poverty rate (a measure of economic disadvantage) and the black population share (a measure of segregation) in the average migrant's destination county also fall modestly in no-network counterfactual. Results are similar when we examine county characteristics as of 1980.[54] Panel B, for Great Plains white migrants, generally shows even smaller changes in destination characteristics. In sum, these results suggest that migration networks had little or no effect on the characteristics of migrants' chosen destination. This is largely because migrants that did not follow their birth town migration network moved to similar places.

One important caveat is that our model does not account for all possible general equilibrium effects. However, the direction of these effects is not clear: reducing migration from a town to a county could make that destination more attractive, because of higher wages or lower housing costs, or less attractive, because of fewer individuals with the same race and background. Our model also does not account for the possibility that destination characteristics, such as the unemployment rate, could change in the counterfactual. Addressing these issues would require a model with labor demand, housing supply, and endogenous amenities, which is beyond the scope of this paper.

6 Conclusion

This paper provides new evidence on the effects of birth town migration networks on location decisions. We use administrative data to study over one million long-run location decisions made during two landmark migration episodes by African Americans born in the U.S. South and whites born in the Great Plains. We formulate a novel network index that characterizes the effect of migration networks for each receiving and sending location. The network index allows us to estimate

[54] Results also are similar when we consider a counterfactual in which Southern black migration networks are as strong as those of Great Plains white migrants.

the overall effect of migration networks and the degree to which network effects are associated with economic characteristics of receiving and sending locations. The network index can be used for other outcomes and settings to provide a deeper understanding of social networks.

We find very strong network effects among Southern black migrants and weaker effects among whites. Estimates of our network index imply that when one randomly chosen African American moves from a birth town to a destination county, then 1.9 additional black migrants make the same move on average. For white migrants from the Great Plains, the average is only 0.4, and results for Southern whites are similarly small. Interpreted through a novel structural model, our estimates imply that 34 percent of black migrants chose their long-run destination because of their birth town migration network, while 13 percent of Great Plains whites were similarly influenced. In addition, our results suggest that black migration networks connected migrants to attractive employment opportunities and played a larger role in less costly moves. Our results also suggest that educational attainment and related factors in the South facilitated migration networks. While the goal of this paper is not to explain the black-white gap, one interpretation of our results is that African Americans relied on migration networks more heavily to overcome greater discrimination in labor and housing markets and a relative lack of resources.

These results shed new light on location decisions. In addition to real wages, amenities, and moving costs, as emphasized by previous work, our results suggest that social networks play a major role in where individuals move. Migration networks appear to help mitigate the substantial information frictions in long-distance location decisions. Networks could play an important role in contemporaneous rural-to-urban migrations in developing nations, which resemble the historical migration episodes we study on several dimensions. Our results also suggest that long-run location decisions will shift labor more effectively to areas with a high marginal product if there are pioneer migrants who can facilitate these moves. Policies that seek to direct migration to certain areas should account for such networks.

Our results also have implications for the effects of migration on destinations. Migration networks continued to operate after location decisions were made, and the Great Migration generated considerable variation in the strength of social networks across destinations. In other work, we use this variation to study the relationship between crime and social connectedness in U.S. cities (Stuart and Taylor, 2018). Examining the importance of migration networks in other settings, and studying other effects of migration networks on destinations, is a valuable direction for future work.

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Table 1: Location at Old Age, 1916-1936 Cohorts

		Percent Living in Location		
		Outside Birth	In Birth Region	
	People	Region	Birth State	Other State
Birth State	(1)	(2)	(3)	(4)
Panel A: Southern Blacks				
Alabama	209,128	47.2%	39.5%	13.3%
Florida	79,237	26.1%	67.1%	6.8%
Georgia	218,357	36.3%	44.2%	19.5%
Louisiana	179,445	32.4%	52.7%	14.9%
Mississippi	218,759	56.1%	28.9%	15.0%
North Carolina	200,999	40.2%	49.7%	10.1%
South Carolina	163,650	43.4%	41.9%	14.7%
Total	1,269,575	41.8%	44.0%	14.1%
Panel B: Great Plains Whites				
Kansas	462,490	30.4%	43.3%	26.3%
Nebraska	374,265	36.0%	42.0%	22.0%
North Dakota	210,199	44.1%	31.8%	24.1%
Oklahoma	635,621	31.8%	41.6%	26.6%
South Dakota	196,266	40.4%	35.4%	24.2%
Total	1,878,841	34.6%	40.3%	25.1%
Panel C: Southern Whites				
Alabama	469,698	9.8%	62.1%	28.1%
Florida	231,071	12.7%	68.5%	18.8%
Georgia	454,286	7.4%	65.5%	27.1%
Louisiana	384,601	8.7%	71.1%	20.2%
Mississippi	275,147	11.0%	57.0%	32.0%
North Carolina	588,674	8.5%	71.6%	19.8%
South Carolina	238,697	6.6%	70.6%	22.8%
Total	2,642,174	9.0%	66.9%	24.0%

Notes: Column 1 contains the number of people from the 1916-1936 birth cohorts observed in the Duke SSA/Medicare data. Columns 2-4 display the share of individuals living in each location at old age (2001 or date of death, if earlier). Figure 2 displays birth regions.

Source: Duke SSA/Medicare data

Table 2: Extreme Examples of Correlated Location Decisions, Southern Blacks and Great Plains Whites

Birth Town (1)	Largest City in Destination County (2)	Total Birth Town Migrants (3)	Town-Destination Flow (4)	Destination Share of Birth Town Migrants (5)	Destination Share of Birth State Migrants (6)	SD under Independent Binomial Moves (7)	Moving Probability Estimate (8)	Network Index Estimate (9)
Panel A: Southern Blacks								
Pigeon Creek, AL	Niagara Falls, NY	85	43	50.6%	0.5%	64.5	4.5%	8.5
Marion, AL	Fort Wayne, IN	1311	200	15.3%	0.7%	63.7	3.8%	8.8
Greeleyville, SC	Troy, NY	215	34	15.8%	0.1%	62.2	1.7%	15.2
Athens, AL	Rockford, IL	649	64	9.9%	0.2%	61.0	2.0%	5.6
Pontotoc, MS	Janesville, WI	456	62	13.6%	0.2%	59.4	3.3%	6.5
New Albany, MS	Racine, WI	599	97	16.2%	0.4%	58.7	4.9%	11.4
West, MS	Freeport, IL	336	35	10.4%	0.1%	56.9	0.8%	6.2
Gatesville, NC	New Haven, CT	176	88	50.0%	1.6%	51.8	8.1%	7.1
Statham, GA	Hamilton, OH	75	22	29.3%	0.3%	50.0	3.0%	4.4
Cochran, GA	Paterson, NJ	259	62	23.9%	0.6%	49.4	4.1%	6.3
Panel B: Great Plains Whites								
Krebs, OK	Akron, OH	210	32	15.2%	0.1%	82.6	0.3%	7.4
Haven, KS	Elkhart, IN	144	22	15.3%	0.1%	51.1	0.4%	6.9
McIntosh, SD	Rupert, ID	299	20	6.7%	0.1%	50.9	0.6%	4.8
Hull, ND	Bellingham, WA	55	24	43.6%	0.5%	44.6	1.5%	4.3
Lindsay, NE	Moline, IL	226	29	12.8%	0.2%	41.5	0.4%	5.2
Corsica, SD	Holland, MI	253	26	10.3%	0.2%	39.6	0.4%	6.3
Corsica, SD	Grand Rapids, MI	253	34	13.4%	0.3%	37.2	0.7%	6.0
Montezuma, KS	Merced, CA	144	21	14.6%	0.3%	32.7	0.9%	2.7
Hillsboro, KS	Fresno, CA	407	65	16.0%	0.9%	32.0	1.2%	2.2
Henderson, NE	Fresno, CA	146	32	21.9%	0.7%	31.1	0.8%	2.2

Notes: Each panel contains the most extreme examples of correlated location decisions, as determined by column 7. Column 7 equals the difference, in standard deviations, of the actual moving propensity (column 5) relative to the prediction with independent moves following a binomial distribution governed by the statewide moving propensity (column 6). Column 8 equals the estimated probability of moving from town j to county k using observed location decisions from nearby towns, where the birth town group is defined by cross validation. Column 9 equals the destination-level network index estimate for the relevant birth state. When choosing these examples, we restrict attention to town-destination pairs with at least 20 migrants.
Source: Duke SSA/Medicare data

Table 3: Average Network Index Estimates, by Birth State

Birth State	Number of Migrants (1)	Unweighted Average (2)	Weighted Average (3)
Panel A: Black Moves out of South			
Alabama	96,269	0.770	1.888
		(0.049)	(0.195)
Florida	19,158	0.536	0.813
		(0.052)	(0.117)
Georgia	77,038	0.735	1.657
		(0.048)	(0.177)
Louisiana	55,974	0.462	1.723
		(0.039)	(0.478)
Mississippi	120,454	0.901	2.303
		(0.050)	(0.313)
North Carolina	78,420	0.566	1.539
		(0.039)	(0.130)
South Carolina	69,399	0.874	2.618
		(0.054)	(0.301)
All States	516,712	0.736	1.938
		(0.020)	(0.110)
Panel B: White Moves out of Great Plains			
Kansas	139,374	0.128	0.255
		(0.007)	(0.024)
Nebraska	134,011	0.141	0.361
		(0.008)	(0.082)
North Dakota	92,205	0.174	0.464
		(0.012)	(0.036)
Oklahoma	200,392	0.112	0.453
		(0.008)	(0.036)
South Dakota	78,541	0.163	0.350
		(0.009)	(0.026)
All States	644,523	0.137	0.380
		(0.004)	(0.022)

Notes: Column 2 is an unweighted average of destination-level network index estimates, $\hat{\Delta}_k$. Column 3 is a weighted average, where the weights are the number of people who move from each state to destination k. Birth town groups are defined by cross validation. Standard errors are in parentheses.
Source: Duke SSA/Medicare data

Table 4: Average Network Index Estimates, with and without Birth Town Covariates

	Include Covariates		p-value of
	No	Yes	difference
Birth State	(1)	(2)	(3)
Panel A: Black Moves out of South			
Alabama	1.888	1.852	0.763
	(0.195)	(0.189)	
Florida	0.813	0.742	0.401
	(0.117)	(0.119)	
Georgia	1.657	1.689	0.658
	(0.177)	(0.175)	
Louisiana	1.723	1.651	0.862
	(0.478)	(0.474)	
Mississippi	2.303	2.295	0.967
	(0.313)	(0.306)	
North Carolina	1.539	1.482	0.149
	(0.130)	(0.127)	
South Carolina	2.618	2.636	0.827
	(0.301)	(0.304)	
All States	1.938	1.917	0.764
	(0.110)	(0.108)	
Panel B: White Moves out of Great Plains			
Kansas	0.255	0.233	0.112
	(0.024)	(0.024)	
Nebraska	0.361	0.349	0.504
	(0.082)	(0.082)	
North Dakota	0.464	0.445	0.456
	(0.036)	(0.035)	
Oklahoma	0.453	0.439	0.241
	(0.036)	(0.036)	
South Dakota	0.350	0.331	0.145
	(0.026)	(0.026)	
All States	0.380	0.363	0.021
	(0.022)	(0.022)	

Notes: All columns contain weighted averages of destination-level network index estimates, $\hat{\Delta}_k$, where the weights are the number of people who move from each state to destination k. Column 2 controls for birth town-level covariates as described in the text. The covariates are an indicator for being along a railroad, an indicator for having above-median black population share, and four indicators corresponding to population quintiles. We construct percentiles for black population share and population separately for each birth state. Column 3 reports the p-value from testing the null hypothesis that the two columns are equal. Birth town groups are defined by cross validation. Standard errors are in parentheses.
Source: Duke SSA/Medicare data

Table 5: Average Network Index Estimates, by Size of Birth Town and Destination

Exclude Largest Birth Towns:	No	Yes	No	Yes
Exclude Largest Destinations:	No	No	Yes	Yes
Birth State	(1)	(2)	(3)	(4)
Panel A: Black Moves out of South				
Alabama	1.888	1.784	2.056	2.189
	(0.195)	(0.149)	(0.285)	(0.268)
Florida	0.813	0.607	1.323	1.231
	(0.117)	(0.061)	(0.229)	(0.215)
Georgia	1.657	1.458	1.696	1.772
	(0.177)	(0.092)	(0.170)	(0.133)
Louisiana	1.723	1.106	0.971	0.960
	(0.478)	(0.095)	(0.182)	(0.176)
Mississippi	2.303	2.299	2.085	2.032
	(0.313)	(0.304)	(0.210)	(0.205)
North Carolina	1.539	1.451	0.743	0.687
	(0.130)	(0.126)	(0.064)	(0.059)
South Carolina	2.618	2.556	1.784	1.742
	(0.301)	(0.283)	(0.241)	(0.234)
All States	1.938	1.791	1.755	1.783
	(0.110)	(0.089)	(0.108)	(0.102)
Panel B: White Moves out of Great Plains				
Kansas	0.255	0.220	0.243	0.228
	(0.024)	(0.019)	(0.021)	(0.019)
Nebraska	0.361	0.253	0.265	0.253
	(0.082)	(0.014)	(0.019)	(0.017)
North Dakota	0.464	0.464	0.527	0.531
	(0.036)	(0.036)	(0.046)	(0.046)
Oklahoma	0.453	0.395	0.450	0.427
	(0.036)	(0.029)	(0.040)	(0.038)
South Dakota	0.350	0.339	0.387	0.381
	(0.026)	(0.026)	(0.034)	(0.033)
All States	0.380	0.331	0.374	0.361
	(0.022)	(0.012)	(0.016)	(0.016)

Notes: All columns contain weighted averages of destination-level network index estimates, $\hat{\Delta}_k$, where the weights are the number of people who move from each state to destination k. Column 1 includes all birth towns and destinations. Column 2 excludes birth towns with 1920 population greater than 20,000 when estimating each $\hat{\Delta}_k$. Column 3 excludes all destination counties which intersect in 2000 with the ten largest non-South CMSAs as of 1950: New York, Chicago, Los Angeles, Philadelphia, Boston, Detroit, Washington D.C., San Francisco, Pittsburgh, and St. Louis, in addition to counties which received fewer than 10 migrants. Column 4 excludes large birth towns and large destinations. Birth town groups are defined by cross validation. Standard errors are in parentheses.
Source: Duke SSA/Medicare data

Table 6: Network Index Estimates and Destination County Characteristics

	Dependent variable: Destination-level network index estimate					
	Black Moves out of South			White Moves out of Plains		
	(1)	(2)	(3)	(4)	(5)	(6)
Manufacturing employment share, 1910	1.583	0.361	0.328	0.025	-0.238	-0.238
	(0.432)	(0.481)	(0.489)	(0.080)	(0.116)	(0.116)
Manufacturing employment share by small destination indicator		2.162	2.190		0.338	0.342
		(0.753)	(0.749)		(0.147)	(0.147)
Agriculture employment share, 1910	0.046	-0.335	-0.362	0.042	0.040	0.036
	(0.229)	(0.408)	(0.412)	(0.035)	(0.102)	(0.102)
Agriculture employment share by small destination indicator		0.562	0.486		0.010	0.018
		(0.459)	(0.474)		(0.108)	(0.108)
Small destination indicator		-0.515	-0.521		-0.015	-0.019
		(0.241)	(0.241)		(0.064)	(0.064)
Log distance from birth state	-0.362	-0.334	-0.315	0.070	0.083	0.075
	(0.061)	(0.063)	(0.061)	(0.037)	(0.038)	(0.039)
Direct railroad connection from birth state	0.315	0.336	0.349	0.218	0.218	0.209
	(0.111)	(0.112)	(0.128)	(0.044)	(0.044)	(0.046)
One-stop railroad connection from birth state	0.225	0.218	0.184	0.091	0.086	0.086
	(0.077)	(0.075)	(0.078)	(0.018)	(0.018)	(0.018)
Log population, 1900	0.102	0.112	0.116	0.010	0.019	0.018
	(0.039)	(0.040)	(0.042)	(0.008)	(0.008)	(0.008)
Percent African American, 1900	-2.037	-1.851	-1.760	-0.239	-0.254	-0.251
	(0.332)	(0.330)	(0.327)	(0.034)	(0.036)	(0.035)
Birth state fixed effects			x			x
R2	0.093	0.103	0.115	0.031	0.035	0.035
N (birth state-destination county pairs)	1,469	1,469	1,469	3,822	3,822	3,822
Destination counties	371	371	371	1,148	1,148	1,148

Notes: The sample contains only counties that received at least 10 migrants. Birth town groups are defined by cross validation. We measure distance from the centroid of destination counties to the centroid of birth states. Standard errors, clustered by destination county, are in parentheses.

Sources: Duke SSA/Medicare data, Haines and ICPSR (2010) data, and Black et al. (2015) data

Table 7: Network Index Estimates and Birth County Characteristics

	Dependent variable: Birth county-level network index estimate			
	Black Moves out of South		White Moves out of Plains	
	(1)	(2)	(3)	(4)
Black/white farm ownership rate, 1920	1.854	2.123	0.948	0.819
	(1.353)	(1.390)	(0.559)	(0.585)
Log black/white population density, 1920	1.099	1.027	0.219	0.258
	(0.562)	(0.565)	(0.112)	(0.121)
Rosenwald school exposure	-0.981	-1.202		
	(0.656)	(0.687)		
Black/white literacy rate, 1920	3.680	5.128	-3.908	-8.238
	(1.574)	(2.094)	(3.122)	(3.484)
Railroad exposure	-0.309	-0.268	-0.150	-0.136
	(0.423)	(0.442)	(0.073)	(0.078)
Percent African American, 1920	0.606	0.880	1.097	1.969
	(1.684)	(1.589)	(1.118)	(1.215)
Birth state fixed effects		x		x
R2	0.090	0.097	0.095	0.147
N (birth counties)	549	549	394	394

Notes: Railroad exposure is the share of migrants in a county that lived along a railroad. Rosenwald exposure is the average Rosenwald coverage experienced over ages 7-13. Heteroskedastic robust standard errors are in parentheses.

Sources: Duke SSA/Medicare data, Haines and ICPSR (2010) data, Aaronson and Mazumder (2011) data, and Black et al. (2015) data

Table 8: Estimated Percent of Migrants That Chose Their Destination Because of Migration Network

	Destination Region				
	All	Northeast	Midwest	West	South
Birth State	(1)	(2)	(3)	(4)	(5)
Panel A: Black Moves out of South					
Alabama	34.3	24.5	40.1	22.5	-
Florida	22.8	24.3	23.4	13.5	-
Georgia	32.9	32.3	36.5	17.0	-
Louisiana	35.0	20.3	29.9	38.7	-
Mississippi	36.0	17.4	39.8	23.3	-
North Carolina	32.2	34.5	21.1	8.3	-
South Carolina	36.8	39.2	26.4	11.0	-
All States	34.2	32.9	37.4	28.5	-
Panel B: White Moves out of Great Plains					
Kansas	9.1	3.1	10.3	10.5	3.4
Nebraska	12.7	4.6	11.6	14.5	4.2
North Dakota	13.9	5.2	10.0	15.7	4.9
Oklahoma	14.5	4.6	8.5	17.3	5.2
South Dakota	12.0	3.7	11.1	13.6	4.0
All States	12.6	4.1	10.3	14.7	4.4

Notes: Table contains migrant-weighted average estimates of $100 \times (N_k^{\text{network}}/N_k)$, the percent of migrants that chose their destination because of their birth town migration network. See the text for details.
Source: Duke SSA/Medicare data

Table 9: Counties with the Five Largest Increases and Decreases in Migration in a Counterfactual without Migration Networks

Destination County (1)	Largest City in Destination County (2)	Actual Number of Migrants (3)	Counterfactual Number of Migrants (4)	Difference (5)	Percent Difference (6)
Panel A: Black Moves out of South					
Queens, NY	New York	12,507	15,148	2,641	21.1
Prince George's, MD	Bowie	7,241	8,959	1,718	23.7
Oakland, MI	Farmington Hills	3,570	4,774	1,204	33.7
Sacramento, CA	Sacramento	2,939	4,128	1,189	40.5
Alameda, CA	Oakland	8,041	9,002	961	12.0
Baltimore City, MD	Baltimore	12,520	9,381	-3,139	-25.1
Philadelphia, PA	Philadelphia	25,007	21,408	-3,599	-14.4
Wayne, MI	Detroit	42,818	38,200	-4,618	-10.8
Los Angeles, CA	Los Angeles	31,703	25,534	-6,169	-19.5
Cook, IL	Chicago	59,915	42,638	-17,277	-28.8
Panel B: White Moves out of Great Plains					
Maricopa, AZ	Phoenix	28,967	29,398	431	1.5
San Bernardino, CA	San Bernardino	13,037	13,453	416	3.2
Pima, AZ	Tucson	8,000	8,383	383	4.8
Mohave, AZ	Lake Havasu City	3,825	4,181	356	9.3
Clark, NV	Las Vegas	9,408	9,755	347	3.7
San Diego, CA	San Diego	19,960	18,739	-1,221	-6.1
San Joaquin, CA	Stockton	7,207	5,653	-1,554	-21.6
Fresno, CA	Fresno	8,329	5,968	-2,361	-28.3
Kern, CA	Bakersfield	10,546	8,134	-2,412	-22.9
Los Angeles, CA	Los Angeles	38,552	30,769	-7,783	-20.2

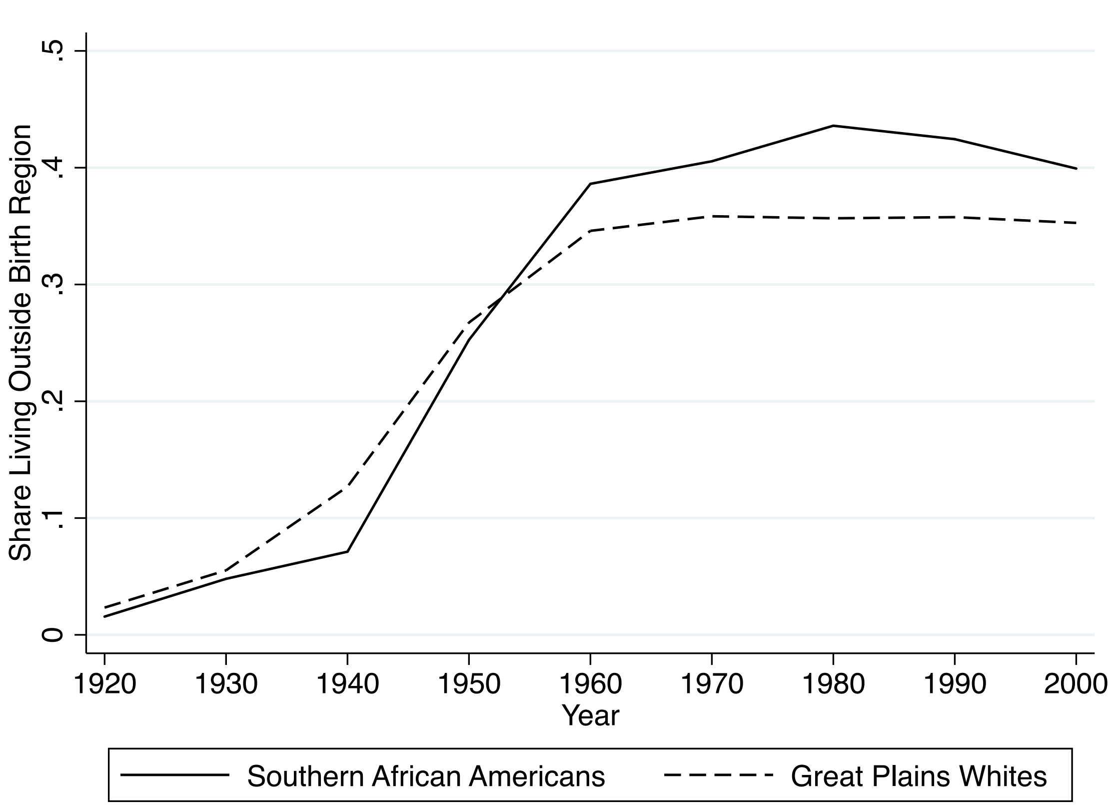
Notes: Column 3 contains N_k, the actual number of migrants in destination k. Column 4 contains estimates of N_k^{cf}, the number of migrants that would have chosen destination county k in the absence of migration networks. Column 6 is equal to column 5 divided by column 3. See the text for details.
Source: Duke SSA/Medicare data

Table 10: Characteristics of Counties where Southern Black Migrants Live Under Realized and Counterfactual Migration Networks

	Realized Networks	No Network Counterfactual		
County Characteristic	Mean (1)	Mean (2)	Mean change, all migrants (3)	Mean change, switchers (4)
Panel A: Black Moves out of South				
Unemployment rate, 2000	7.50	7.27	-0.23	-0.67
Poverty rate, 2000	14.79	14.28	-0.51	-1.48
Percent black, 2000	25.17	23.70	-1.47	-4.26
Unemployment rate, 1980	8.12	7.95	-0.17	-0.49
Poverty rate, 1980	13.64	13.15	-0.49	-1.42
Percent black, 1980	22.68	21.13	-1.55	-4.49
Panel B: Whites Moves out of Great Plains				
Unemployment rate, 2000	6.61	6.70	0.09	0.71
Poverty rate, 2000	6.64	6.53	-0.11	-0.87
Percent black, 2000	12.68	12.48	-0.20	-1.58
Unemployment rate, 1980	6.02	6.05	0.03	0.24
Poverty rate, 1980	7.34	7.32	-0.02	-0.16
Percent black, 1980	11.21	11.17	-0.04	-0.32

Notes: Column 1 contains the migrant-weighted average of county characteristics based on the realized location decisions of migrants. Column 2 contains the migrant-weighted average based on the location decisions that would be made in the absence of migration networks. Column 3 is the difference between column 2 and column 1. Column 4 reports the mean change for migrants that would switch their location under the counterfactual, calculated as column 3 divided by the percent of migrants that would switch their location (34.5 percent in Panel A and 12.7 percent in Panel B). See the text for details.
Source: Duke SSA/Medicare data

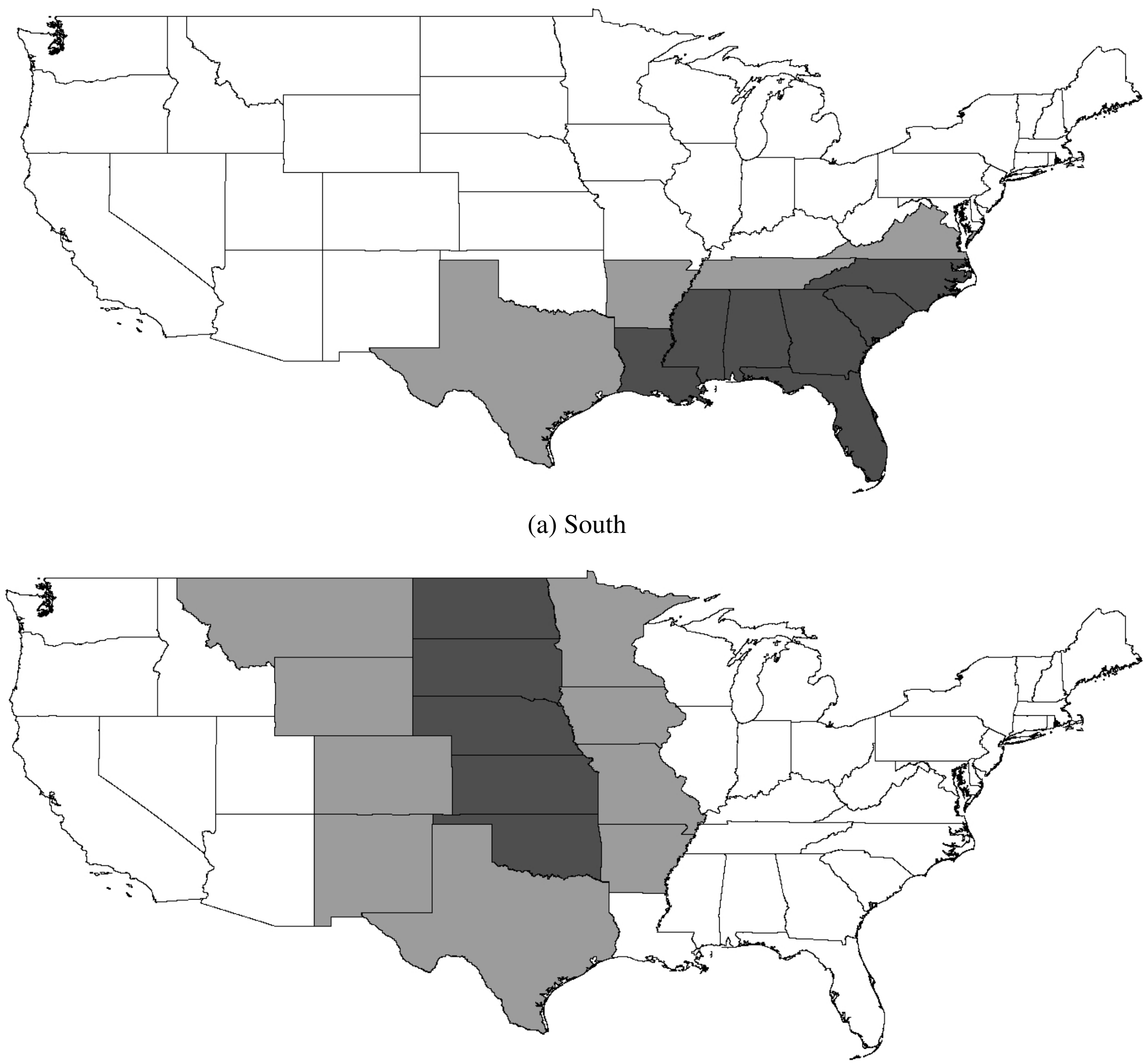
Figure 1: Share Living Outside Birth Region, 1916-1936 Cohorts, by Year



Notes: The solid line shows the percent of African Americans born from 1916-1936 in the seven Southern birth states we analyze (dark grey states in Figure 2a) living outside the South (light and dark grey states) at the time of Census enumeration. The dashed line shows the percent of whites born from 1916-1936 from the Great Plains states living outside the Great Plains or Border States.

Source: Ruggles et al. (2010) data

Figure 2: Geographic Coverage

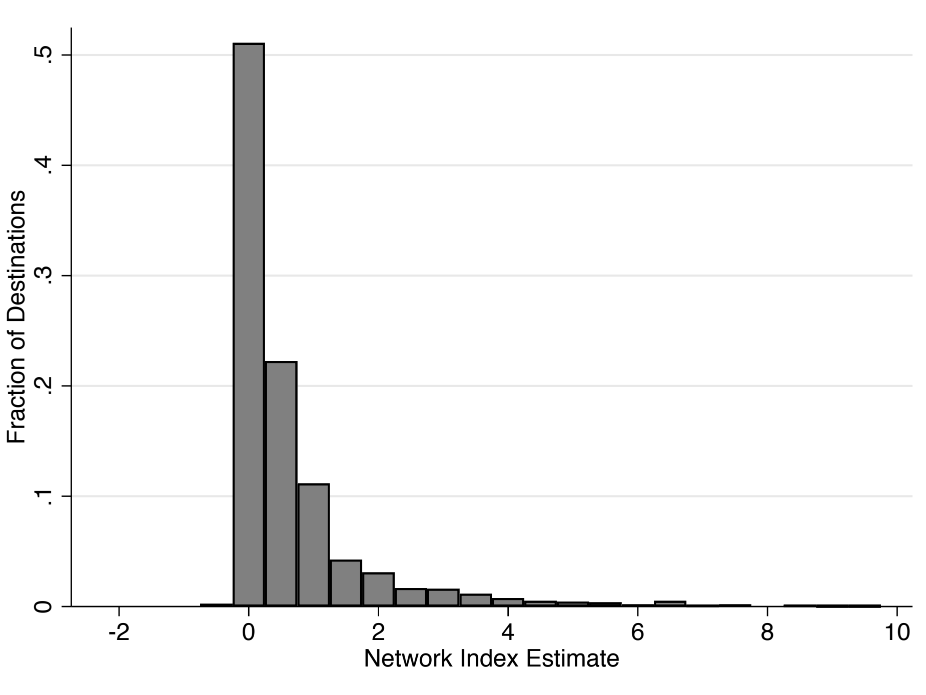


(a) South

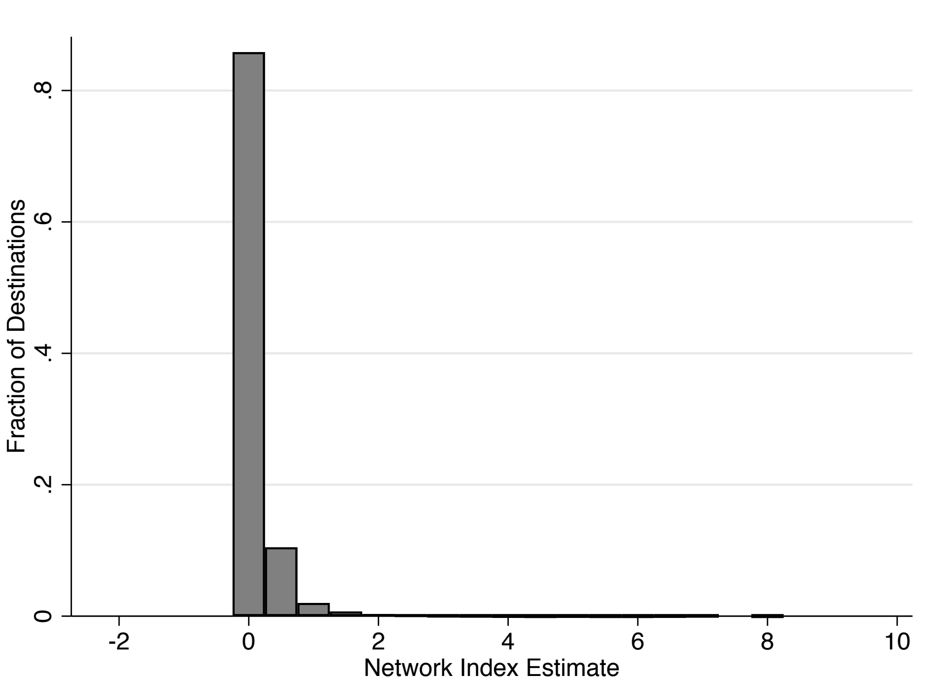
(b) Great Plains

Notes: For the South, our sample includes migrants born in the seven states in dark grey (Alabama, Georgia, Florida, Louisiana, Mississippi, North Carolina, South Carolina). A migrant is someone who at old age lives outside of the former Confederate states, which are the dark and light grey states. For the Great Plains, our sample includes migrants born in the five states in dark grey (Kansas, Nebraska, North Dakota, Oklahoma, South Dakota). A migrant is someone who at old age lives outside of the Great Plains states and the surrounding border area.

Figure 3: Distribution of Destination-Level Network Index Estimates



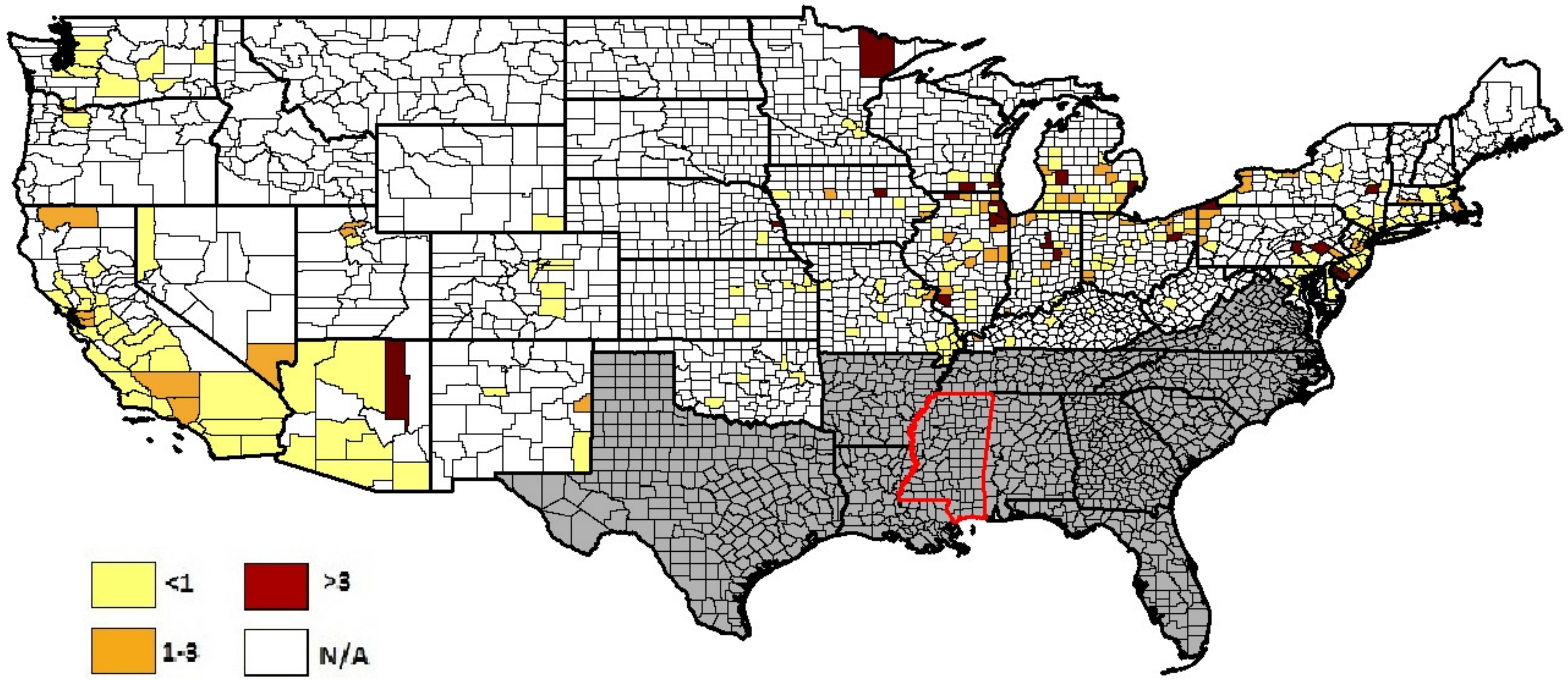
(a) Black Moves out of South



(b) White Moves out of Great Plains

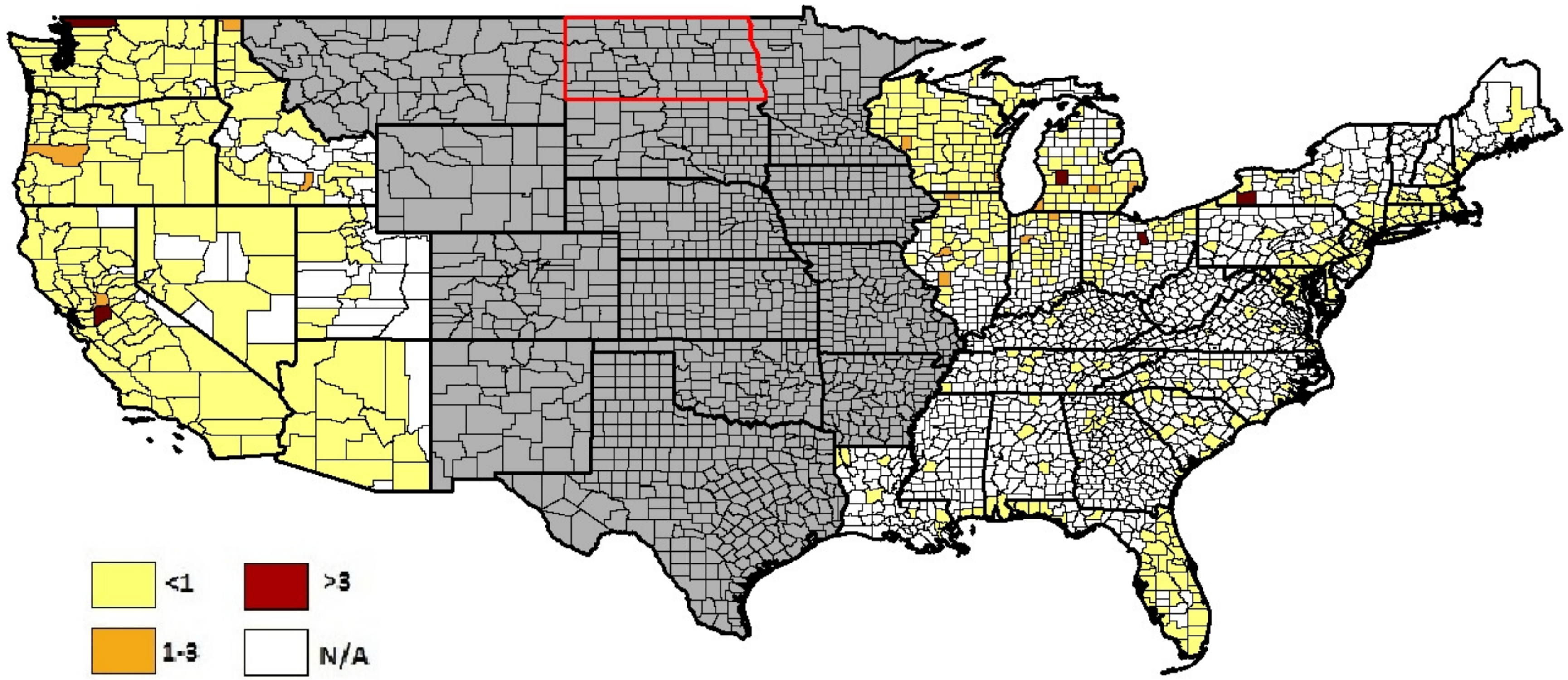
Notes: Bin width is 1/2. Birth town groups are defined by cross validation. Panel (a) omits the estimate $\hat{\Delta}_k = 11.4$ from Mississippi to Racine County, WI, $\hat{\Delta}_k = 15.2$ from South Carolina to Rensselaer County, NY, and $\hat{\Delta}_k = 18.1$ from Florida to St. Joseph County, IN.
Source: Duke SSA/Medicare data

Figure 4: Spatial Distribution of Destination-Level Network Index Estimates, Mississippi-born Blacks



Notes: Figure displays destination-level network index estimates, $\hat{\Delta}_k$, across U.S. counties for Mississippi-born black migrants. The South is shaded in grey, with Mississippi outlined in red. Destinations to which less than 10 migrants moved are in white. Among all African American estimates, $\hat{\Delta}_k = 3$ corresponds to the 95th percentile, and $\hat{\Delta}_k = 1$ corresponds to the 81st percentile.
Source: Duke SSA/Medicare data

Figure 5: Spatial Distribution of Destination-Level Network Index Estimates, North Dakota-born Whites



Notes: See note to Figure 4. Among all Great Plains white estimates, $\hat{\Delta}_k = 3$ is greater than the 99th percentile, and $\hat{\Delta}_k = 1$ corresponds to the 98th percentile.
Source: Duke SSA/Medicare data

Appendices

A Derivation of Network Index

Appendix A derives the expression for the network index in equation (4).

First, recall the definition of the network index, $\Delta_{j,k} \equiv \mathbb{E}[N_{-i,j,k}|D_{i,j,k}=1]-\mathbb{E}[N_{-i,j,k}|D_{i,j,k}=0]$. Because $\mathbb{E}[N_{-i,j,k}|\cdot]=(N_j-1)\,\mathbb{E}[D_{i',j,k}|\cdot]$ for $i'\neq i$, we can rewrite this as

$$\Delta_{j,k}=(N_j-1)\left(\mathbb{E}[D_{i',j,k}|D_{i,j,k}=1]-\mathbb{E}[D_{i',j,k}|D_{i,j,k}=0]\right),\; i'\neq i. \tag{A.1}$$

The law of iterated expectations implies that the probability of moving from birth town j to destination k can be written

$$P_{j,k}=\mathbb{E}[D_{i',j,k}|D_{i,j,k}=1]P_{j,k}+\mathbb{E}[D_{i',j,k}|D_{i,j,k}=0](1-P_{j,k}). \tag{A.2}$$

Using the definition $\mu_{j,k}\equiv\mathbb{E}[D_{i',j,k}|D_{i,j,k}=1]$ and rearranging equation (A.2) yields

$$\mathbb{E}[D_{i',j,k}|D_{i,j,k}=0]=\frac{P_{j,k}(1-\mu_{j,k})}{1-P_{j,k}}. \tag{A.3}$$

Hence, we have

$$\mathbb{E}[D_{i',j,k}|D_{i,j,k}=1]-\mathbb{E}[D_{i',j,k}|D_{i,j,k}=0]=\mu_{j,k}-\frac{P_{j,k}(1-\mu_{j,k})}{1-P_{j,k}} \tag{A.4}$$

$$=\frac{\mu_{j,k}-P_{j,k}}{1-P_{j,k}}. \tag{A.5}$$

Substituting equation (A.5) into equation (A.1) yields

$$\Delta_{j,k}=(N_j-1)\left(\frac{\mu_{j,k}-P_{j,k}}{1-P_{j,k}}\right). \tag{A.6}$$

Applying the law of iterated expectations to the first term of the covariance of location decisions, $C_{j,k}$, yields

$$C_{j,k}\equiv\mathbb{E}[D_{i',j,k}D_{i,j,k}]-\mathbb{E}[D_{i',j,k}]\,\mathbb{E}[D_{i,j,k}] \tag{A.7}$$

$$=\mathbb{E}[D_{i',j,k}|D_{i,j,k}=1]P_{j,k}-(P_{j,k})^2 \tag{A.8}$$

Using the definition of $\mu_{j,k}$ and rearranging yields $\mu_{j,k}-P_{j,k}=C_{j,k}/P_{j,k}$. Substituting this expression into (A.6), and noting that Assumption 1 implies that $P_{j,k}=P_{g,k}$, yields equation (4).

B Generalized Method of Moments Formulation

B.1 Basic Model

As described in the text, we can derive the destination-level network index, Δ_k, in two ways: as a weighted average of $\Delta_{j,k}$ or by assuming that for each destination $\Delta_{j,k}$ is constant across birth towns within a birth state. Both approaches lead to the same point estimate of the destination-level network index, but the latter approach allows us to use GMM to estimate standard errors.

If we assume that the network index, $\Delta_{j,k}$, is constant across birth towns within a birth state, the destination-level network index, Δ_k, can be written

$$\Delta_k = \Delta_{j,k} = \frac{C_{j,k}(N_j - 1)}{P_{j,k} - P_{j,k}^2}. \tag{A.9}$$

It is useful to rewrite this as

$$\Delta_k \left(P_{j,k} - P_{j,k}^2\right) - C_{j,k}(N_j - 1) = 0. \tag{A.10}$$

To conduct inference, we treat the birth town group as the unit of observation. Aggregating across towns within a birth town group yields

$$\Delta_k Y_{g,k} - X_{g,k} = 0, \tag{A.11}$$

where

$$X_{g,k} \equiv \sum_{j \in g} C_{j,k}(N_j - 1) \tag{A.12}$$

$$Y_{g,k} \equiv \sum_{j \in g} P_{j,k} - P_{j,k}^2. \tag{A.13}$$

In the text, we describe how we construct our estimates $\widehat{P_{j,k}}$, $\widehat{P_{j,k}^2}$, and $\widehat{C_{j,k}}$. These estimates immediately lead to estimates $\widehat{X_{g,k}}$ and $\widehat{Y_{g,k}}$, which can be written as deviations from the underlying parameters,

$$\widehat{X_{g,k}} = X_{g,k} + u_{g,k}^X \tag{A.14}$$

$$\widehat{Y_{g,k}} = Y_{g,k} + u_{g,k}^Y. \tag{A.15}$$

This allows us to rewrite equation (A.11),

$$\Delta_k \widehat{Y_{g,k}} - \widehat{X_{g,k}} + (\Delta_k u_{g,k}^Y - u_{g,k}^X) = 0. \tag{A.16}$$

Because we have unbiased estimates of $P_{j,k}$, $P_{j,k}^2$, and $C_{j,k}$, we have unbiased estimates of $X_{g,k}$ and $Y_{g,k}$. This implies that

$$\mathbb{E}\left[\Delta_k \widehat{Y_{g,k}} - \widehat{X_{g,k}}\right] = 0. \tag{A.17}$$

Equation (A.17) is the basis of our GMM estimator. The sample analog is

$$\frac{1}{G}\sum_g \left(\widehat{\Delta_k}\widehat{Y_{g,k}} - \widehat{X_{g,k}}\right) = 0, \tag{A.18}$$

where G is the number of birth town groups in a state. This can be rewritten

$$\widehat{\Delta_k} = \frac{\sum_j \widehat{C_{j,k}}(N_j - 1)}{\sum_{j'} \widehat{P_{j',k}} - \widehat{P^2_{j',k}}}. \tag{A.19}$$

Equation (A.19) is identical to equation (8).

The above derivation is for a single destination-level network index, but can easily be expanded to consider all K destination-level network index parameters. The aggregated moment condition is

$$\mathbb{E}\begin{bmatrix} \Delta_1\widehat{Y_{g,1}} - \widehat{X_{g,1}} \\ \vdots \\ \Delta_K\widehat{Y_{g,K}} - \widehat{X_{g,K}} \end{bmatrix} \equiv \mathbb{E}\left[\boldsymbol{f}(\boldsymbol{w}_g, \boldsymbol{\Delta})\right] = \boldsymbol{0}, \tag{A.20}$$

where $\boldsymbol{w}_g$ is observed data used to construct $\widehat{\boldsymbol{X_g}}$ and $\widehat{\boldsymbol{Y_g}}$ and $\boldsymbol{\Delta} \equiv (\Delta_1, \ldots, \Delta_K)'$ is a $K \times 1$ vector of destination-level network index parameters.

Under standard conditions (e.g., Cameron and Trivedi, 2005), the asymptotic distribution of $\boldsymbol{\Delta}$ is

$$\sqrt{G}(\hat{\boldsymbol{\Delta}} - \boldsymbol{\Delta}) \xrightarrow{d} \mathcal{N}\left[\boldsymbol{0}, \hat{\boldsymbol{F}}^{-1}\hat{\boldsymbol{S}}(\hat{\boldsymbol{F}}')^{-1}\right], \tag{A.21}$$

where

$$\hat{\boldsymbol{F}} = \frac{1}{G}\sum_g \left.\frac{\partial \boldsymbol{f}_g}{\partial \boldsymbol{\Delta}'}\right|_{\hat{\boldsymbol{\Delta}}} \tag{A.22}$$

$$= \frac{1}{G}\sum_g \begin{bmatrix} \widehat{Y_{g,1}} & 0 & 0 & \cdots & 0 \\ 0 & \widehat{Y_{g,2}} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \cdots & \widehat{Y_{g,K}} \end{bmatrix} \tag{A.23}$$

and

$$\hat{\boldsymbol{S}} = \frac{1}{G}\sum_g \boldsymbol{f}(\boldsymbol{W}_g, \hat{\boldsymbol{\Delta}})\boldsymbol{f}(\boldsymbol{W}_g, \hat{\boldsymbol{\Delta}})'. \tag{A.24}$$

While it is convenient to describe the asymptotic properties when grouping all destinations together into $\boldsymbol{\Delta}$, we estimate each destination-level network index parameter Δ_k independently.

B.2 Comparing Estimates from Two Models

The GMM framework facilitates a comparison of estimates from different models. Under the null hypothesis we wish to test, we have two unbiased estimates for $X_{g,k}$ and $Y_{g,k}$:

$$\widehat{X^1_{g,k}} = X_{g,k} + u^X_{g,k} \tag{A.25}$$
$$\widehat{Y^1_{g,k}} = Y_{g,k} + u^Y_{g,k} \tag{A.26}$$
$$\widehat{X^2_{g,k}} = X_{g,k} + v^X_{g,k} \tag{A.27}$$
$$\widehat{Y^2_{g,k}} = Y_{g,k} + v^Y_{g,k}. \tag{A.28}$$

We estimate the unrestricted version of the model using GMM, for which the sample analog of the moment condition is

$$\frac{1}{G}\sum_g \begin{pmatrix} \widehat{\Delta^1_k}\widehat{Y^1_{g,k}} - \widehat{X^1_{g,k}} \\ \widehat{\Delta^2_k}\widehat{Y^2_{g,k}} - \widehat{X^2_{g,k}} \end{pmatrix} \tag{A.29}$$

This simply stacks the two estimates of the destination-level network index, Δ_k into a single, exactly-identified system.

Let $\Delta^1 \equiv N^{-1}\sum_k N_k \Delta_k$ be the migrant-weighted average of the destination-level network index parameters, where $N \equiv \sum_k N_k$ is the total number of migrants from a birth state. We are interested in testing whether $\Delta^1 = \Delta^2$. To test this hypothesis, we form the test statistic

$$\hat{t} = \frac{\widehat{\Delta^1} - \widehat{\Delta^2}}{\left(\widehat{\mathbb{V}}[\widehat{\Delta^1} - \widehat{\Delta^2}]\right)^{1/2}}. \tag{A.30}$$

Given destination-level network index estimates $\widehat{\Delta^1_k}$ and $\widehat{\Delta^2_k}$, it is straightforward to construct the averages $\widehat{\Delta^1}$ and $\widehat{\Delta^2}$. To estimate the variance in the denominator of the test statistic, we assume that destination-level network index estimates are independent of each other. Given the large number of sending birth towns, and the large number of destinations, we believe that the covariance between two destination-level network index estimates is likely small. Furthermore, we are not confident in our ability to reliably estimate the covariance of the covariances of location decisions, as would be necessary if we did not assume independence. Under the independence assumption, we can estimate $\widehat{\mathbb{V}}[\widehat{\Delta^1} - \widehat{\Delta^2}]$ as the appropriately weighted sum of

$$\widehat{\mathbb{V}}[\widehat{\Delta^1_k} - \widehat{\Delta^2_k}] = \widehat{\mathbb{V}}[\widehat{\Delta^1_k}] + \widehat{\mathbb{V}}[\widehat{\Delta^2_k}] - 2\widehat{\mathbb{C}}[\widehat{\Delta^1_k}, \widehat{\Delta^2_k}] \tag{A.31}$$

which we obtain from the GMM variance estimate.

C Estimating Cross-Group Network Indices

When estimating cross-group network indices, we are interested in the expected increase in the number of type b people from birth town j that move to destination county k when an arbitrarily chosen person i of type w is observed to make the same move,

$$\Delta_{j,k}^{b|w} \equiv \mathbb{E}[N_{j,k}^{b}|D_{i,j,k}^{w}=1]-\mathbb{E}[N_{j,k}^{b}|D_{i,j,k}^{w}=0]. \tag{A.32}$$

The steps described in Appendix A yield

$$\Delta_{j,k}^{b|w} = \frac{C_{j,k}^{b,w}N_{j}^{b}}{P_{j,k}^{w}(1-P_{j,k}^{w})}, \tag{A.33}$$

where $C_{j,k}^{b,w}$ is the covariance of location decisions between migrants of type b and w, N_j^b is the number of type b migrants born in j, and $P_{j,k}^{w}$ is the probability that a migrant of type w moves from j to k.

We estimate $P_{j,k}^{w}$ as described in the text. To estimate $C_{j,k}^{b,w}$, consider the model

$$D_{i,j(i),k}^{b}D_{i',j(i'),k}^{w} = \alpha_{g,k} + \sum_{j\in g}\beta_{j,k}^{b,w}1[j(i)=j(i')=j]+\epsilon_{i,i',k}. \tag{A.34}$$

This model is analogous to equation (1) in the text and yields the following covariance estimator,

$$\widehat{C_{j,k}^{b,w}} = \frac{N_{j,k}^{b}N_{j,k}^{w}}{N_{j}^{b}N_{j}^{w}} - \frac{\sum_{j\in g}\sum_{j'\neq j\in g}N_{j,k}^{b}N_{j',k}^{w}}{\sum_{j\in g}\sum_{j'\neq j\in g}N_{j}^{b}N_{j'}^{w}}. \tag{A.35}$$

We estimate the destination-level network index as

$$\hat{\Delta}_{k}^{b|w} = \sum_{j}\left(\frac{\widehat{P_{j,k}^{w}}-\widehat{(P_{j,k}^{w})^2}}{\sum_{j'}\widehat{P_{j',k}^{w}}-\widehat{(P_{j',k}^{w})^2}}\right)\hat{\Delta}_{j,k}^{b|w}. \tag{A.36}$$

We only estimate network indices for destinations which received at least ten black and white migrants from a given state. When calculating weighted averages of $\hat{\Delta}_{k}^{b|w}$, we use the number of type w individuals who moved to each destination.

D Addressing Measurement Error due to Incomplete Migration Data

Network index estimates depend on population flows observed in the Duke SSA/Medicare data, which is incomplete because some individuals die before enrolling in Medicare and some individuals' birth town information is unavailable. We first address the consequences of measurement error due to incomplete migration data under a missing at random assumption. If we observe a random sample of migration flows for each birth town-destination pair, then measurement error does not bias estimates of the covariance of location decisions, $C_{j,k}$, or moving probabilities, $P_{g,k}$. As a result, equation (4) implies that network index estimates will be attenuated because we undercount the number of migrants from each town, N_j.

More specifically, let N_j^* be the true number of migrants from birth town j that live to age 65, let α be the coverage rate, and assume that

$$N_j = \alpha N_j^*. \tag{A.37}$$

We approximate the coverage rate by dividing the number of individuals in the Duke SSA/Medicare data by the number of individuals in decennial census data who are born from 1916-1936 and survive to age 65.[55] The overall coverage rate is 64.9 percent for African Americans from the South and 82.2 percent for whites from the Great Plains (Appendix Table A.9), which implies that $N_j^* \approx 1.54N_j$ for Southern African Americans and $N_j^* \approx 1.22N_j$ for Great Plains whites. As an approximate measurement error correction, network index estimates should be multiplied by factors of 1.54 and 1.22 for Southern black and Great Plains white migrants. Appendix Table A.10 presents results that reflect state-specific coverage rate adjustments. The weighted average of destination-level network index estimates is 3.06 for Southern African Americans and 0.46 for Great Plains whites. Adjusting for incomplete data under a missing at random assumption increases both the magnitude of network index estimates and the black-white gap.

An alternative approach is to define N_j^* as the true number of migrants that live to a younger age, such as 40. Under this benchmark, coverage rates would be lower, and the estimates that adjust for measurement error would be larger. We do not focus on this alternative because, as described in the text, our data are best-suited for measuring long-run location decisions for individuals who survive to age 65.

Without making a missing at random (MAR) assumption, we can derive a lower bound on the network index and show that estimates of this lower bound still reveal sizable migration networks. As described in the text, the network index, $\Delta_{j,k}$, depends on the covariance of location decisions for migrants from birth town j to destination k, $C_{j,k}$, the probability of moving from birth town group g to destination k, $P_{g,k}$, and the number of migrants from town j, N_j. To focus on the key issues, suppose that we have an unbiased estimate of $P_{g,k}$ and consider the consequences of measurement error in $C_{j,k}$ and N_j. Let $\Delta_{j,k}^*$ and $C_{j,k}^*$ be the true values of the network index and covariance of location decisions. The true parameters are connected through the equation

$$\Delta_{j,k}^* = \frac{C_{j,k}^*(N_j^* - 1)}{P_{g,k} - P_{g,k}^2}. \tag{A.38}$$

Using the definition of covariance, it is straightforward to show that

$$C_{j,k}^* = \alpha^2 C_{j,k} + 2\alpha(1-\alpha)C_{j,k}^{\text{in, out}} + (1-\alpha)^2 C_{j,k}^{\text{out, out}}, \tag{A.39}$$

where $C_{j,k}$ is the covariance of location decisions between migrants who are in our data, $C_{j,k}^{\text{in, out}}$ is the average covariance of location decisions between a migrant who is in our data and a migrant who is not, and $C_{j,k}^{\text{out, out}}$ is the average covariance of location decisions between migrants who are not in our data.

When not assuming that data are MAR, the covariance of location decisions among migrants not in our data ($C_{j,k}^{\text{in, out}}$ and $C_{j,k}^{\text{out, out}}$) could differ from the covariance of location decisions between migrants who are in our data ($C_{j,k}$). As a result, the network index based on our data, $\Delta_{j,k}$,

[55] We use the 1990 Census to construct coverage rates for individuals born from 1916-1925 and the 2000 Census for individuals born from 1926-1935.

might not simply be attenuated, as implied by the MAR assumption. In general, we cannot point identify the network index under this more general measurement error model. However, we can construct a lower bound for the strength of migration networks. In particular, we make the extreme assumptions that there are no interactions between migrants in and out of our data, so that $C_{j,k}^{\text{in, out}} = 0$, and that there are no interactions between migrants out of our data, so that $C_{j,k}^{\text{out, out}} = 0$. In this case, equations (A.37), (A.38), and (A.39) imply that

$$\Delta^*_{j,k} \geq \alpha \Delta_{j,k}, \tag{A.40}$$

so that we can estimate a lower bound on the true network index by multiplying the estimated network index by the coverage rate.[56] Combining the average coverage rates (64.9 and 82.2 percent) with the average destination-level network index estimates from Table 3, we estimate a lower bound for the network index of 1.26 for African Americans and 0.31 for whites. These lower bounds, which depend on extremely conservative assumptions about the migration of individuals not in our data, still reveal sizable networks, especially among African Americans.

E Differences in Family Size and the Black-White Gap

Appendix E provides a more detailed discussion of whether differences in family size explain the black-white network index gap.

To explore this issue, we decompose the network index into a component for migrants from the same family, Δ^{fam}, and a component for migrants not from the same family, Δ^{not}. To examine the importance of differences in family size, we assume that black and white network indices differ only because of differences in family size. Then we have

$$\Delta_b = \Delta^{fam} P_b^{fam} + \Delta^{not}(1 - P_b^{fam}) \tag{A.41}$$

$$\Delta_w = \Delta^{fam} P_w^{fam} + \Delta^{not}(1 - P_w^{fam}), \tag{A.42}$$

where Δ_b is the network index among black migrants, and P_b^{fam} is the probability that two randomly chosen black migrants are from the same family. Δ_w and P_w^{fam} are defined analogously. The black-white network index gap is

$$\Delta_b - \Delta_w = (\Delta^{fam} - \Delta^{not})(P_b^{fam} - P_w^{fam}). \tag{A.43}$$

Our data do not allow us to estimate $\Delta^{fam} - \Delta^{not}$, but we can use equation (A.43), along

[56] Proof: If $C_{j,k}^{\text{in, out}} = C_{j,k}^{\text{out, out}} = 0$, equations (A.37), (A.38), and (A.39) imply

$$\begin{aligned}\Delta^*_{j,k} &= \frac{\alpha^2 C_{j,k}\left(\frac{N_j}{\alpha} - 1\right)}{P_{g,k} - P_{g,k}^2} \\ &\geq \frac{\alpha^2 C_{j,k}\left(\frac{N_j}{\alpha} - \frac{1}{\alpha}\right)}{P_{g,k} - P_{g,k}^2} = \alpha \Delta_{j,k},\end{aligned}$$

where the inequality comes from noting that $\alpha \in [0, 1]$ and assuming $C_{j,k} \geq 0$, and the final equality comes from equation (4) in the text. One could also construct upper bounds, but these are not particularly informative.

with estimates of $\Delta_b - \Delta_w$ and $P_b^{fam} - P_w^{fam}$ to explore whether it is reasonable to conclude that differences in family size explain the black-white gap. As described in the text, our average network indices for black and white migrants are 1.94 and 0.38. In the 1940 Census, the average within-household family size for individuals born from 1916-1936 is 6.16 for African Americans from the South and 5.25 for whites from the Great Plains. In the Duke SSA/Medicare dataset, there are 142 black migrants and 181 white migrants per town. However, as discussed in the text, the Duke data undercount the total number of migrants. If we inflate the migrant counts by 1.54 and 1.22, then we estimate 219 black migrants and 221 white migrants per town. Combining the Census family size estimates with the adjusted Duke migrant estimates, we have $P_b^{fam} = 6.16/219 = 0.028$ and $P_w^{fam} = 5.25/221 = 0.024$. With these estimates, $\Delta^{fam} - \Delta^{not}$ would have to equal 520 ($= 1.56/0.003$) people for differences in family size to fully explain the black-white gap. This is clearly implausible.

To construct an upper bound on the probability that two randomly chosen migrants are from the same family, we use the 100 percent sample of the 1940 Census to count the number of individuals in a county born from 1916-1936 with the same last name (Minnesota Population Center and Ancestry.com, 2013). On average, there are 54.5 African Americans with the same last name and 14.7 whites with the same last name. Using these numbers in the numerator leads to estimates of $P_b^{fam} = 54.5/219 = 0.249$ and $P_w^{fam} = 14.7/221 = 0.067$. In this case, $\Delta^{fam} - \Delta^{not}$ would have to equal 8.57 ($= 1.56/0.182$) people for differences in family size to fully explain the black-white gap. This approach considerably overestimates the extent of family connections, because many individuals with the same last name are not related, and we use counties, instead of towns, as the geographic unit in the numerator of P^{fam}. Even still, this gap seems too large to us. In sum, differences in family size might explain some, but not all, of the differences in migration networks between black and white migrants.

Table A.1: Industry of Migrants and Non-Migrants, Southern Blacks and Great Plains Whites, 1950

	Percent of Group Working in Industry			
	Southern Blacks		Great Plains Whites	
	Migrants (1)	Non-Migrants (2)	Migrants (3)	Non-Migrants (4)
Agriculture, Forestry, and Fishing	1.23%	35.92%	9.38%	31.60%
Mining	1.33%	1.21%	2.02%	3.65%
Construction	10.19%	8.12%	11.98%	9.14%
Manufacturing	37.87%	22.09%	23.79%	10.98%
Transportation, Communication, and Other Utilities	11.80%	7.89%	9.58%	9.59%
Wholesale and Retail Trade	13.61%	10.46%	16.47%	16.87%
Finance, Insurance, and Real Estate	2.21%	0.78%	2.39%	2.20%
Business and Repair Services	2.98%	1.67%	4.11%	3.49%
Personal Services	6.30%	5.24%	2.16%	1.83%
Entertainment and Recreation Services	1.03%	0.63%	1.15%	0.76%
Professional and Related Services	3.95%	3.31%	5.67%	4.27%
Public Administration	6.57%	2.33%	11.08%	5.17%
Other	0.92%	0.35%	0.22%	0.43%

Note: Sample contains currently employed males, age 20-60 in the 1950 Census.
Source: Ruggles et al. (2010)

Table A.2: Size of Birth Town Groups Chosen by Cross Validation

Birth State	(1)
Panel A: Southern Blacks	
Alabama	52
Florida	138
Georgia	40
Louisiana	48
Mississippi	42
North Carolina	52
South Carolina	30
Panel B: Great Plains Whites	
Kansas	128
Nebraska	128
North Dakota	84
Oklahoma	68
South Dakota	112
Panel C: Southern Whites	
Alabama	156
Florida	270
Georgia	168
Louisiana	136
Mississippi	170
North Carolina	50
South Carolina	266

Notes: Column 1 displays the results of a cross validation procedure that chooses the length of the square grid used to define birth town groups. See text for details. Source: Duke SSA/Medicare data

Table A.3: Number of Birth Towns and Migrants, by Birth State

Birth State	Birth Towns (1)	Migrants (2)	Migrants Per Town (3)
Panel A: Black Moves out of South			
Alabama	693	96,269	138.9
Florida	203	19,158	94.4
Georgia	566	77,038	136.1
Louisiana	460	55,974	121.7
Mississippi	660	120,454	182.5
North Carolina	586	78,420	133.8
South Carolina	461	69,399	150.5
All States	3,629	516,712	142.4
Panel B: White Moves out of Great Plains			
Kansas	883	139,374	157.8
Nebraska	643	134,011	208.4
North Dakota	592	92,205	155.8
Oklahoma	966	200,392	207.4
South Dakota	474	78,541	165.7
All States	3,558	644,523	181.1

Notes: Sample limited to towns with at least 10 migrants in the data.
Source: Duke SSA/Medicare data

Table A.4: Average Destination-Level Network Index Estimates, Birth Town Groups Defined by Cross Validation and Counties

	Cross Validation		Counties	
Type of Average: Birth State	Unweighted (1)	Weighted (2)	Unweighted (3)	Weighted (4)
Panel A: Black Moves out of South				
Alabama	0.770	1.888	0.616	1.393
	(0.049)	(0.195)	(0.034)	(0.170)
Florida	0.536	0.813	0.597	0.811
	(0.052)	(0.117)	(0.087)	(0.317)
Georgia	0.735	1.657	0.544	0.887
	(0.048)	(0.177)	(0.039)	(0.279)
Louisiana	0.462	1.723	0.399	2.209
	(0.039)	(0.478)	(0.039)	(0.920)
Mississippi	0.901	2.303	0.742	2.166
	(0.050)	(0.313)	(0.051)	(0.401)
North Carolina	0.566	1.539	0.402	1.022
	(0.039)	(0.130)	(0.028)	(0.123)
South Carolina	0.874	2.618	0.774	2.132
	(0.054)	(0.301)	(0.049)	(0.224)
All States	0.736	1.938	0.599	1.608
	(0.020)	(0.110)	(0.017)	(0.151)
Panel B: White Moves out of Great Plains				
Kansas	0.128	0.255	0.106	0.194
	(0.007)	(0.024)	(0.008)	(0.028)
North Dakota	0.174	0.464	0.156	0.385
	(0.012)	(0.036)	(0.010)	(0.029)
Nebraska	0.141	0.361	0.121	0.399
	(0.008)	(0.082)	(0.009)	(0.117)
Oklahoma	0.112	0.453	0.102	0.372
	(0.008)	(0.036)	(0.007)	(0.036)
South Dakota	0.163	0.350	0.135	0.273
	(0.009)	(0.026)	(0.008)	(0.027)
All States	0.137	0.380	0.119	0.329
	(0.004)	(0.022)	(0.004)	(0.028)

Notes: Columns 1 and 3 are unweighted averages of destination-level network index estimates, $\hat{\Delta}_k$. Columns 2 and 4 are weighted averages, where the weights are the number of people who move from each state to destination k. In columns 1 and 2, we define birth town groups using cross validation, as described in the text. In columns 3 and 4, we use counties. Standard errors in parentheses.
Source: Duke SSA/Medicare data

Table A.5: Average Network Index Estimates, White Moves out of South

Birth State	Number of Migrants (1)	Unweighted Average (2)	Weighted Average (3)
Alabama	43,157	0.204	0.516
		(0.014)	(0.052)
Florida	27,426	0.046	0.072
		(0.006)	(0.100)
Georgia	31,299	0.082	0.117
		(0.007)	(0.021)
Louisiana	31,303	0.122	0.269
		(0.011)	(0.071)
Mississippi	28,001	0.118	0.186
		(0.010)	(0.021)
North Carolina	47,146	0.179	0.412
		(0.012)	(0.040)
South Carolina	14,605	0.068	0.094
		(0.005)	(0.029)
All States	222,937	0.131	0.280
		(0.004)	(0.021)

Notes: Column 2 is an unweighted average of destination-level network index estimates, $\hat{\Delta}_k$. Column 3 is a weighted average, where the weights are the number of people who move from each state to destination k. Birth town groups are defined by cross validation. Standard errors in parentheses.
Source: Duke SSA/Medicare data

Table A.6: Average Network Index Estimates, By Size of Birth Town and Destination, White Moves out of South

Exclude Largest Birth Towns:	No	Yes	No	Yes
Exclude Largest Destinations:	No	No	Yes	Yes
Birth State	(1)	(2)	(3)	(4)
Alabama	0.516	0.458	0.531	0.481
	(0.052)	(0.045)	(0.071)	(0.062)
Florida	0.072	0.074	0.134	0.030
	(0.100)	(0.012)	(0.082)	(0.009)
Georgia	0.117	0.101	0.119	0.088
	(0.021)	(0.012)	(0.019)	(0.013)
Louisiana	0.269	0.207	0.198	0.143
	(0.071)	(0.022)	(0.035)	(0.017)
Mississippi	0.186	0.185	0.135	0.134
	(0.021)	(0.022)	(0.013)	(0.013)
North Carolina	0.412	0.395	0.337	0.319
	(0.040)	(0.037)	(0.040)	(0.034)
South Carolina	0.094	0.090	0.058	0.055
	(0.029)	(0.023)	(0.013)	(0.012)
All States	0.280	0.254	0.262	0.223
	(0.021)	(0.013)	(0.021)	(0.015)

Notes: All columns contain weighted averages of destination-level network index estimates, $\hat{\Delta}_k$, where the weights are the number of people who move from each state to destination k. Column 1 includes all birth towns and destinations. Column 2 excludes birth towns with 1920 population greater than 20,000 when estimating each $\hat{\Delta}_k$. Column 3 excludes all destination counties which intersect in 2000 with the ten largest non-South CMSAs as of 1950: New York, Chicago, Los Angeles, Philadelphia, Boston, Detroit, Washington D.C., San Francisco, Pittsburgh, and St. Louis, in addition to counties which received fewer than 10 migrants. Column 4 excludes large birth towns and large destinations. Birth town groups are defined by cross validation. Standard errors are in parentheses.
Source: Duke SSA/Medicare data

Table A.7: Average Cross-Race Network Index Estimates, Southern White and Black Migrants

Birth State	All Counties (1)	Excluding Largest CMSAs (2)
Panel A: Blacks Induced to Location by White Migrant		
Alabama	0.188	0.130
	(0.106)	(0.150)
Florida	0.026	0.005
	(0.059)	(0.036)
Georgia	-0.028	0.040
	(0.039)	(0.044)
Louisiana	-0.066	0.068
	(0.196)	(0.038)
Mississippi	0.246	0.049
	(0.185)	(0.033)
North Carolina	-0.010	-0.005
	(0.062)	(0.011)
South Carolina	0.197	-0.025
	(0.161)	(0.027)
All States	0.071	0.050
	(0.048)	(0.033)
Panel B: Whites Induced to Location by Black Migrant		
Alabama	0.052	0.038
	(0.048)	(0.042)
Florida	0.047	-0.018
	(0.064)	(0.036)
Georgia	-0.020	0.004
	(0.014)	(0.014)
Louisiana	-0.137	0.016
	(0.066)	(0.017)
Mississippi	-0.056	0.020
	(0.030)	(0.011)
North Carolina	0.021	-0.002
	(0.029)	(0.022)
South Carolina	-0.019	0.020
	(0.013)	(0.018)
All States	-0.019	0.019
	(0.015)	(0.013)

Notes: Table A.7 contains weighted averages of cross-race destination-level network index estimates. Birth town groups are defined by cross validation. Standard errors in parentheses.
Source: Duke SSA/Medicare data

Table A.8: Average Destination-Level Network Index Estimates, Birth Town Groups Defined by Different Values of Grid Size

	Weighted Average			Unweighted Average		
Grid Size:	50	100	200	50	100	200
Birth State	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Black Moves out of South						
Alabama	1.869	2.256	2.398	0.759	0.846	0.913
	(0.203)	(0.198)	(0.196)	(0.046)	(0.046)	(0.045)
Florida	0.919	0.856	0.944	0.595	0.553	0.560
	(0.196)	(0.117)	(0.117)	(0.158)	(0.087)	(0.055)
Georgia	1.760	2.190	2.421	0.780	0.859	0.916
	(0.163)	(0.185)	(0.168)	(0.055)	(0.053)	(0.049)
Louisiana	1.887	2.097	2.660	0.469	0.508	0.549
	(0.542)	(0.507)	(0.717)	(0.038)	(0.034)	(0.035)
Mississippi	2.432	2.778	3.216	0.910	1.001	1.056
	(0.327)	(0.270)	(0.217)	(0.049)	(0.048)	(0.042)
North Carolina	1.557	1.719	1.877	0.566	0.629	0.678
	(0.133)	(0.149)	(0.139)	(0.041)	(0.043)	(0.037)
South Carolina	3.255	3.620	4.080	0.982	1.074	1.156
	(0.380)	(0.348)	(0.280)	(0.054)	(0.052)	(0.045)
All states	2.090	2.401	2.713	0.761	0.834	0.891
	(0.120)	(0.109)	(0.112)	(0.020)	(0.019)	(0.017)
Panel B: White Moves out of Great Plains						
Kansas	0.256	0.256	0.253	0.122	0.127	0.130
	(0.028)	(0.026)	(0.019)	(0.010)	(0.008)	(0.006)
Nebraska	0.366	0.373	0.379	0.130	0.142	0.146
	(0.090)	(0.079)	(0.062)	(0.008)	(0.008)	(0.008)
North Dakota	0.424	0.490	0.529	0.164	0.177	0.186
	(0.032)	(0.037)	(0.038)	(0.011)	(0.011)	(0.011)
Oklahoma	0.425	0.488	0.514	0.107	0.115	0.119
	(0.038)	(0.038)	(0.034)	(0.008)	(0.008)	(0.007)
South Dakota	0.291	0.343	0.365	0.149	0.162	0.169
	(0.024)	(0.024)	(0.026)	(0.011)	(0.010)	(0.009)
All states	0.360	0.396	0.413	0.128	0.138	0.143
	(0.024)	(0.022)	(0.018)	(0.004)	(0.004)	(0.004)

Notes: Columns 1-3 are weighted averages of destination-level network index estimates, $\widehat{\Delta}_k$, where the weights are the number of people who move from each state to destination k. Columns 4-6 are unweighted averages. We define birth town groups as square grids, with the length of each square varying from 50 to 200 miles. Standard errors in parentheses.
Source: Duke SSA/Medicare data

Table A.9: Coverage Rates, Duke SSA/Medicare Dataset

Sample:	All	All	All	Men	Women	Cohort 1916-25	Cohort 1926-36
Birth State	Duke/SSA coverage rate, all (1)	Duke/SSA percent with town identified (2)	Duke/SSA coverage rate, town identified (3)	Duke/SSA coverage rate, town identified (4)	Duke/SSA coverage rate, town identified (5)	Duke/SSA coverage rate, town identified (6)	Duke/SSA coverage rate, town identified (7)
Panel A: Southern Blacks							
Alabama	86.4%	78.7%	68.0%	73.1%	64.6%	65.1%	70.4%
Florida	82.7%	83.6%	69.2%	72.3%	66.9%	65.5%	72.1%
Georgia	85.0%	73.1%	62.2%	65.2%	60.2%	57.0%	67.5%
Louisiana	85.2%	84.5%	72.0%	74.3%	70.3%	67.5%	76.0%
Mississippi	88.9%	74.7%	66.4%	69.7%	64.1%	63.9%	68.6%
North Carolina	88.5%	72.5%	64.2%	64.6%	63.9%	61.5%	66.5%
South Carolina	90.8%	61.9%	56.2%	57.3%	55.5%	53.6%	58.7%
All States	87.2%	74.4%	64.9%	67.6%	63.1%	61.3%	68.1%
Panel B: Great Plains Whites							
Kansas	88.1%	92.5%	81.5%	84.8%	78.6%	78.6%	84.4%
Nebraska	89.2%	93.3%	83.2%	87.5%	79.6%	80.8%	85.7%
North Dakota	88.1%	89.7%	79.0%	81.9%	76.7%	74.3%	84.0%
Oklahoma	93.1%	89.9%	83.7%	86.0%	81.8%	79.4%	87.7%
South Dakota	88.9%	91.2%	81.1%	82.6%	79.8%	78.7%	83.5%
All States	90.1%	91.3%	82.2%	85.2%	79.8%	78.8%	85.6%

Notes: Column 1 reports the number of individuals in the Duke SSA/Medicare dataset divided by the number of individuals in the 1990/2000 Census. Column 2 reports the share of individuals in the Duke SSA/Medicare dataset for whom birth town and destination county is identified. Columns 3-7 reports the number of individuals in the Duke SSA/Medicare dataset for whom birth town and destination county is identified divided by the number of individuals in the 1990/2000 Census. We use the 1990 Census for individuals born from 1916-1925 and the 2000 Census for individuals born from 1926-1936. The sample includes individuals living inside and outside their birth region.

Source: Duke SSA/Medicare data and Ruggles et al. (2010) data

Table A.10: Average Network Index Estimates, Adjusted for Incomplete Migration Data

Sample: Birth State	All (1)	Men (2)	Women (3)	1916-25 Cohort (4)	1926-36 Cohort (5)
Panel A: Black Moves out of South					
Alabama	2.776	1.160	1.621	1.274	1.672
	(0.287)	(0.120)	(0.175)	(0.145)	(0.165)
Florida	1.175	0.533	0.633	0.454	0.780
	(0.170)	(0.085)	(0.128)	(0.102)	(0.123)
Georgia	2.664	0.959	1.722	1.570	1.287
	(0.284)	(0.111)	(0.205)	(0.213)	(0.118)
Louisiana	2.393	1.184	0.991	0.973	1.676
	(0.664)	(0.316)	(0.389)	(0.225)	(0.573)
Mississippi	3.468	1.456	2.043	1.396	2.236
	(0.471)	(0.202)	(0.297)	(0.211)	(0.307)
North Carolina	2.398	1.029	1.404	1.215	1.326
	(0.203)	(0.100)	(0.121)	(0.115)	(0.109)
South Carolina	4.659	1.935	2.761	2.363	2.478
	(0.535)	(0.199)	(0.381)	(0.310)	(0.260)
All States	3.057	1.271	1.790	1.464	1.792
	(0.167)	(0.071)	(0.109)	(0.086)	(0.108)
Panel B: White Moves out of Great Plains					
Kansas	0.313	0.151	0.178	0.204	0.167
	(0.029)	(0.016)	(0.017)	(0.020)	(0.014)
Nebraska	0.433	0.176	0.256	0.270	0.234
	(0.098)	(0.050)	(0.050)	(0.057)	(0.046)
North Dakota	0.587	0.250	0.338	0.387	0.277
	(0.046)	(0.021)	(0.031)	(0.032)	(0.021)
Oklahoma	0.541	0.250	0.291	0.285	0.319
	(0.043)	(0.023)	(0.023)	(0.025)	(0.026)
South Dakota	0.431	0.187	0.248	0.266	0.225
	(0.032)	(0.017)	(0.021)	(0.022)	(0.018)
All States	0.463	0.205	0.262	0.278	0.252
	(0.026)	(0.014)	(0.014)	(0.016)	(0.013)

Notes: Table A.10 reports weighted averages of destination-level network index estimates, adjusted for incomplete migration data using the coverage rates in Appendix Table A.9. Birth town groups are defined by cross validation. Standard errors in parentheses.
Source: Duke SSA/Medicare data

Table A.11: Summary Statistics, Destination County Characteristics

Variable	Mean	S.D.
Panel A: Black Moves out of South (N=1469)		
Network index estimate, $\widehat{\Delta_k}$	0.732	1.373
Manufacturing employment share, 1910	0.240	0.140
Agriculture employment share, 1910	0.223	0.168
Direct railroad connection from birth state	0.093	0.291
One-stop railroad connection from birth state	0.557	0.497
Log distance from birth state	6.684	0.517
Log population, 1900	11.004	1.105
Percent African American, 1900	0.045	0.082
Small destination indicator	0.608	0.488
Panel B: White Moves out of Great Plains (N=3822)		
Network index estimate, $\widehat{\Delta_k}$	0.140	0.441
Manufacturing employment share, 1910	0.169	0.134
Agriculture employment share, 1910	0.400	0.232
Direct railroad connection from birth state	0.112	0.315
One-stop railroad connection from birth state	0.504	0.500
Log distance from birth state	6.788	0.355
Log population, 1900	10.122	1.080
Percent African American, 1900	0.121	0.197
Small destination indicator	0.849	0.358
Panel C: White Moves Out of South (N=3153)		
Network index estimate, $\widehat{\Delta_k}$	0.131	0.566
Manufacturing employment share, 1910	0.195	0.141
Agriculture employment share, 1910	0.312	0.199
Direct railroad connection from birth state	0.084	0.278
One-stop railroad connection from birth state	0.492	0.500
Log distance from birth state	6.766	0.593
Log population, 1900	10.418	1.143
Percent African American, 1900	0.038	0.077
Small destination indicator	0.752	0.432

Notes: The unit of observation is a birth state-destination county pair. Sample includes destination counties that existed from 1900-2000 and for which we estimate a network index.

Sources: Duke SSA/Medicare data, Haines and ICPSR (2010) data

Table A.12: Network Index Estimates and Destination County Characteristics, Birth Town Groups Defined by Counties

	Dependent variable: Destination-level network index estimate					
	Black Moves out of South			White Moves out of Plains		
	(1)	(2)	(3)	(4)	(5)	(6)
Manufacturing employment share, 1910	1.492	0.053	0.034	0.021	-0.315	-0.316
	(0.636)	(0.412)	(0.416)	(0.069)	(0.137)	(0.137)
Manufacturing employment share by small destination indicator		2.535	2.519		0.424	0.427
		(0.983)	(0.946)		(0.154)	(0.154)
Agriculture employment share, 1910	0.044	-0.507	-0.531	0.027	-0.032	-0.037
	(0.202)	(0.392)	(0.398)	(0.030)	(0.109)	(0.109)
Agriculture employment share by small destination indicator		0.802	0.739		0.074	0.080
		(0.485)	(0.501)		(0.114)	(0.114)
Small destination indicator		-0.650	-0.643		-0.085	-0.089
		(0.287)	(0.279)		(0.069)	(0.069)
Direct railroad connection from birth state	0.349	0.372	0.396	0.170	0.167	0.160
	(0.115)	(0.118)	(0.146)	(0.035)	(0.036)	(0.037)
One-stop railroad connection from birth state	0.222	0.215	0.195	0.068	0.062	0.063
	(0.092)	(0.089)	(0.096)	(0.015)	(0.014)	(0.014)
Log distance from birth state	-0.245	-0.214	-0.223	0.049	0.052	0.045
	(0.072)	(0.080)	(0.065)	(0.028)	(0.029)	(0.029)
Log population, 1900	0.084	0.092	0.089	0.012	0.017	0.017
	(0.046)	(0.045)	(0.051)	(0.007)	(0.007)	(0.007)
Percent African American, 1900	-1.541	-1.315	-1.317	-0.196	-0.206	-0.203
	(0.289)	(0.341)	(0.305)	(0.029)	(0.030)	(0.030)
Birth state fixed effects			x			x
R2	0.055	0.065	0.074	0.029	0.033	0.033
N (birth state-destination county pairs)	1,469	1,469	1,469	3,822	3,822	3,822
Destination counties	371	371	371	1,148	1,148	1,148

Notes: The sample contains only counties that received at least 10 migrants. Birth town groups are defined by counties. We measure distance from the centroid of destination counties to the centroid of birth states. Standard errors, clustered by destination county, are in parentheses.

Sources: Duke SSA/Medicare data, Haines and ICPSR (2010) data, and Black et al. (2015) data

Table A.13: Network Index Estimates and Destination County Characteristics, White Moves out of South

Dependent variable: Destination-level network index estimate	(1)	(2)	(3)
Manufacturing employment share, 1910	0.433	-0.004	0.027
	(0.164)	(0.130)	(0.131)
Manufacturing employment share by small destination indicator		0.602	0.595
		(0.250)	(0.250)
Agriculture employment share, 1910	0.080	0.123	0.157
	(0.045)	(0.144)	(0.144)
Agriculture employment share by small destination indicator		-0.039	-0.061
		(0.156)	(0.154)
Small destination indicator		-0.150	-0.143
		(0.074)	(0.073)
Direct railroad connection from birth state	0.069	0.074	0.087
	(0.041)	(0.041)	(0.040)
One-stop railroad connection from birth state	0.059	0.052	0.060
	(0.022)	(0.021)	(0.021)
Log distance from birth state	-0.042	-0.047	-0.011
	(0.019)	(0.019)	(0.020)
Log population, 1900	-0.010	-0.009	-0.001
	(0.013)	(0.012)	(0.012)
Percent African American, 1900	-0.264	-0.354	-0.272
	(0.095)	(0.099)	(0.096)
Birth state fixed effects			x
R2	0.013	0.018	0.028
N (birth state-destination county pairs)	3,153	3,153	3,153
Destination counties	728	728	728

Notes: The sample contains only counties that received at least 10 migrants. Birth town groups are defined by cross validation. Standard errors, clustered by destination county, are in parentheses.

Sources: Duke SSA/Medicare data, Haines and ICPSR (2010) data, and Black et al. (2015) data

Table A.14: Summary Statistics, Birth County Characteristics

Variable	Mean	S.D.
Panel A: Black Moves out of South (N=549)		
Network index estimate, $\widehat{\Delta_c}$	1.721	3.544
Black farm ownership rate, 1920	0.318	0.246
Log black density, 1920	2.534	1.055
Rosenwald school exposure	0.204	0.217
Black literacy rate, 1920	0.705	0.093
Railroad exposure	0.542	0.405
Percent black, 1920	0.408	0.209
Panel B: White Moves out of Great Plains (N=394)		
Network index estimate, $\widehat{\Delta_c}$	0.352	0.636
White farm ownership rate, 1920	0.576	0.131
Log white density, 1920	2.476	1.006
White literacy rate, 1920	0.992	0.012
Railroad exposure	0.524	0.395
Percent black, 1920	0.017	0.041
Panel C: White Moves Out of South (N=560)		
Network index estimate, $\widehat{\Delta_c}$	0.207	0.774
White farm ownership rate, 1920	0.605	0.155
Log white density, 1920	3.028	0.776
White literacy rate, 1920	0.935	0.054
Railroad exposure	0.535	0.413
Percent black, 1920	0.397	0.212

Notes: Sample includes birth counties containing at least one town with at least 10 migrants in the Duke data. Railroad exposure is the share of migrants in a county that lived along a railroad. Rosenwald school exposure is the average Rosenwald coverage experienced over ages 7-13.
Sources: Duke SSA/Medicare data, Haines and ICPSR (2010) data, Aaronson and Mazumder (2011) data, and Black et al. (2015) data

Table A.15: Network Index Estimates and Birth County Characteristics, White Moves out of South

Dependent variable: Birth county-level network index estimate	(1)	(2)
White farm ownership rate, 1920	-0.488	-0.545
	(0.332)	(0.330)
Log white population density, 1920	-0.216	-0.290
	(0.098)	(0.123)
White literacy rate, 1920	-0.108	0.555
	(0.523)	(0.578)
Railroad exposure	0.039	0.094
	(0.067)	(0.069)
Percent black, 1920	-1.279	-1.492
	(0.274)	(0.309)
Birth state fixed effects		x
R2	0.081	0.104
N (birth counties)	560	560

Notes: Railroad exposure is the share of migrants in a county that lived along a railroad. Heteroskedastic robust standard errors are in parentheses. Sources: Duke SSA/Medicare data, Haines and ICPSR (2010) data, Aaronson and Mazumder (2011) data, and Black et al. (2015) data

Table A.16: Average Network Index Estimates, by Destination Region

	Destination Region			
	Northeast (1)	Midwest (2)	West (3)	South (4)
Panel A: Black Moves out of South				
Alabama	1.237	2.356	0.813	-
	(0.161)	(0.295)	(0.272)	-
Florida	0.978	0.793	0.264	-
	(0.172)	(0.169)	(0.107)	-
Georgia	1.546	2.067	0.410	-
	(0.243)	(0.310)	(0.205)	-
Louisiana	0.282	1.138	2.169	-
	(0.101)	(0.206)	(0.734)	-
Mississippi	0.924	2.662	1.036	-
	(0.105)	(0.396)	(0.130)	-
North Carolina	1.678	0.908	0.185	-
	(0.149)	(0.176)	(0.040)	-
South Carolina	2.907	1.223	0.211	-
	(0.351)	(0.167)	(0.055)	-
All States	1.860	2.259	1.402	-
	(0.120)	(0.195)	(0.345)	-
Panel B: White Moves out of Great Plains				
Kansas	0.079	0.452	0.281	0.051
	(0.019)	(0.095)	(0.031)	(0.006)
Nebraska	0.080	0.439	0.420	0.063
	(0.014)	(0.096)	(0.109)	(0.009)
North Dakota	0.107	0.405	0.524	0.047
	(0.027)	(0.057)	(0.046)	(0.009)
Oklahoma	0.051	0.390	0.542	0.074
	(0.007)	(0.091)	(0.047)	(0.007)
South Dakota	0.061	0.485	0.381	0.058
	(0.013)	(0.069)	(0.034)	(0.011)
All States	0.073	0.434	0.442	0.062
	(0.007)	(0.039)	(0.029)	(0.004)

Notes: All columns contain weighted averages of destination-level network index estimates, $\hat{\Delta}_k$, where the weights are the number of people who move from each state to destination k. We define destination regions slightly differently than the Census Bureau because we treat the former Confederate states as the South. The Census South region includes Delaware, the District of Columbia, Maryland, West Virginia, Kentucky, and Oklahoma. We include the first four states in the Northeast and the latter two in the Midwest. We do not estimate network indices for African Americans who move to the South. Birth town groups are defined by cross validation. Standard errors are in parentheses.
Source: Duke SSA/Medicare data

Table A.17: Average Network Index Estimates, by Destination Region, White Moves out of South

	Destination Region			
	Northeast (1)	Midwest (2)	West (3)	South (4)
Alabama	0.140	1.048	0.208	-
	(0.021)	(0.123)	(0.034)	-
Florida	0.090	0.070	0.277	-
	(0.017)	(0.020)	(0.104)	-
Georgia	0.104	0.307	0.082	-
	(0.013)	(0.049)	(0.023)	-
Louisiana	0.159	0.450	0.331	-
	(0.027)	(0.100)	(0.100)	-
Mississippi	0.067	0.301	0.127	-
	(0.014)	(0.052)	(0.014)	-
North Carolina	0.549	0.489	0.302	-
	(0.063)	(0.122)	(0.048)	-
South Carolina	0.111	0.081	0.073	-
	(0.011)	(0.012)	(0.022)	-
All States	0.275	0.534	0.220	-
	(0.024)	(0.044)	(0.026)	-

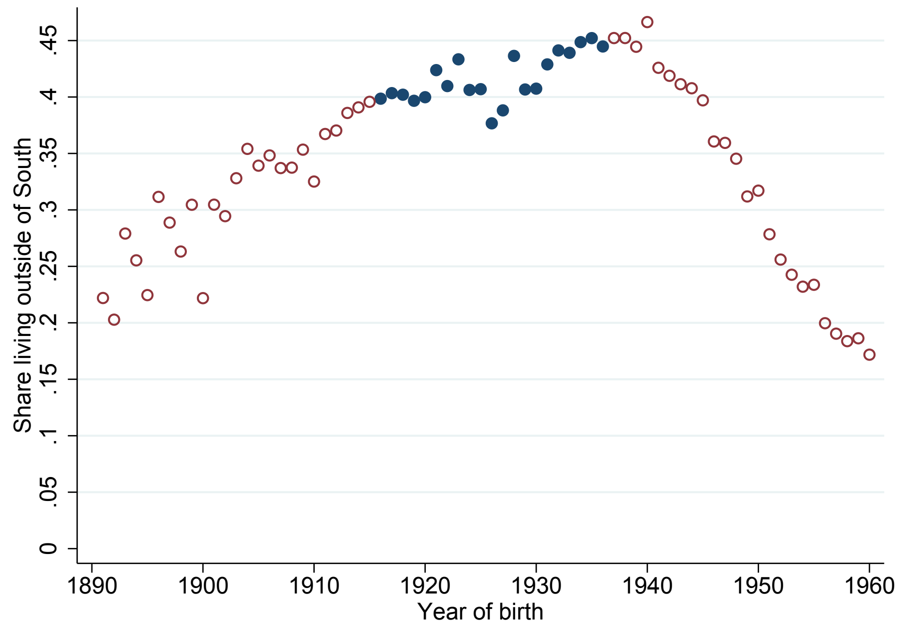
Notes: See note to Appendix Table A.16. Standard errors are in parentheses.
Source: Duke SSA/Medicare data

Table A.18: Changes in Regional Migration Patterns in a Counterfactual without Migration Networks

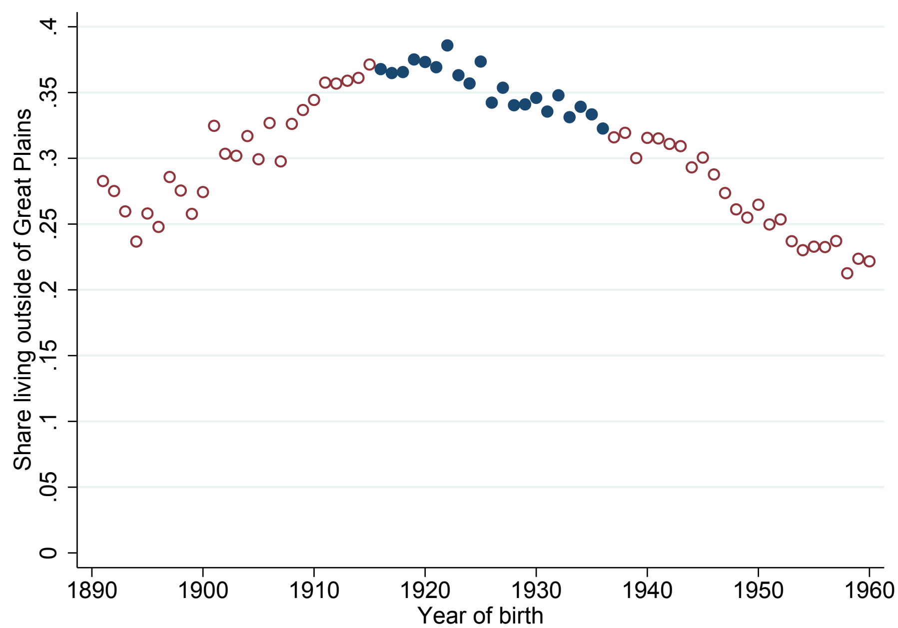
	Destination Region			
	Northeast	Midwest	West	South
Birth State	(1)	(2)	(3)	(4)
Panel A: Black Moves out of South				
Alabama	4,354	-6,706	2,353	
	[19.2%]	[-10.8%]	[20.5%]	
Florida	-224	-68	291	
	[-1.8%]	[-1.7%]	[12.2%]	
Georgia	621	-2,147	1,526	
	[1.6%]	[-6.6%]	[25.4%]	
Louisiana	1,267	1,809	-3,076	
	[31.2%]	[11.7%]	[-8.4%]	
Mississippi	2,951	-7,303	4,352	
	[38.9%]	[-7.6%]	[25.5%]	
North Carolina	-2,252	1,033	1,220	
	[-3.3%]	[14.9%]	[36.9%]	
South Carolina	-2,175	1,056	1,119	
	[-3.6%]	[14.8%]	[43.5%]	
All States	4,541	-12,325	7,785	
	[2.1%]	[-5.5%]	[9.8%]	
Panel B: White Moves out of Great Plains				
Kansas	485	-179	-1,645	1,339
	[6.9%]	[-1.1%]	[-1.7%]	[6.6%]
Nebraska	673	284	-2,462	1,505
	[10.7%]	[2.0%]	[-2.5%]	[10.9%]
North Dakota	305	527	-1,508	676
	[10.0%]	[4.6%]	[-2.1%]	[10.4%]
Oklahoma	819	995	-5,000	3,186
	[12.2%]	[7.4%]	[-3.3%]	[11.3%]
South Dakota	292	171	-1,126	662
	[9.7%]	[1.5%]	[-2.0%]	[9.4%]
All States	2,574	1,799	-11,740	7,368
	[9.9%]	[2.7%]	[-2.5%]	[9.7%]

Notes: Table contains estimates of N_k^{cf}, the number of migrants that would have chosen destination county k in the absence of migration network, aggregated over all counties in each region. Percent changes of the number of migrants in the counterfactual are in brackets. See the text for details. Source: Duke SSA/Medicare data

Figure A.1: Migration Rates Around Ages 40-49



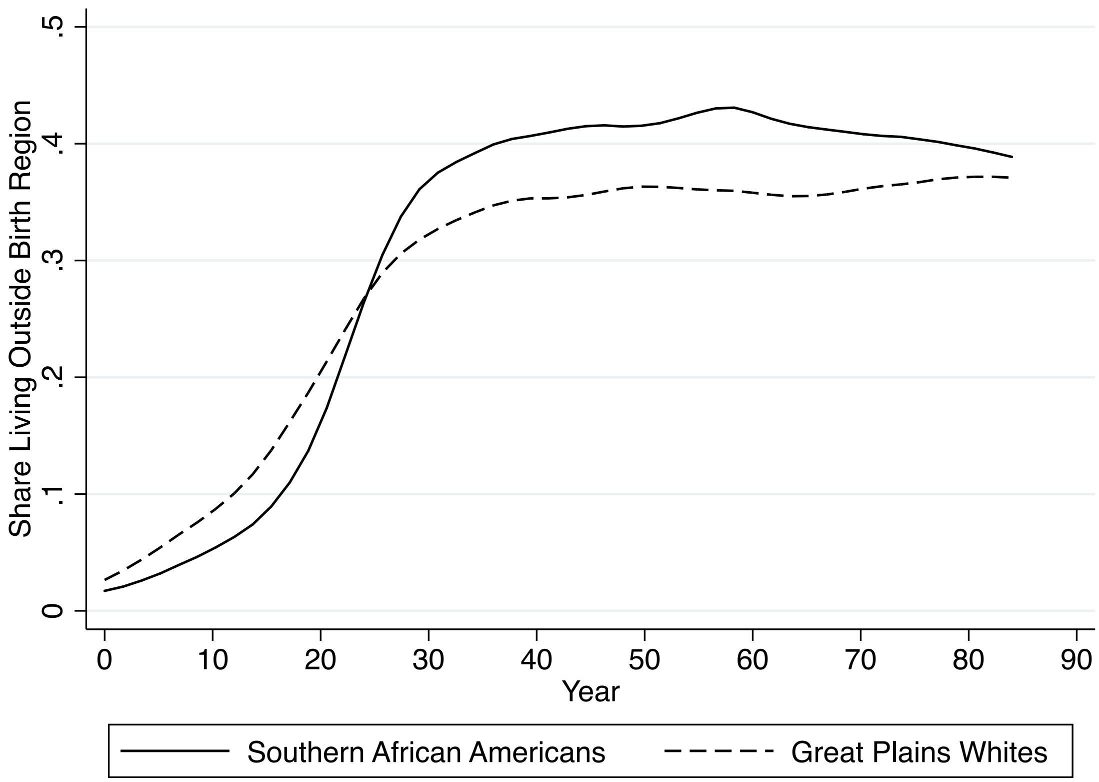
(a) South



(b) Great Plains

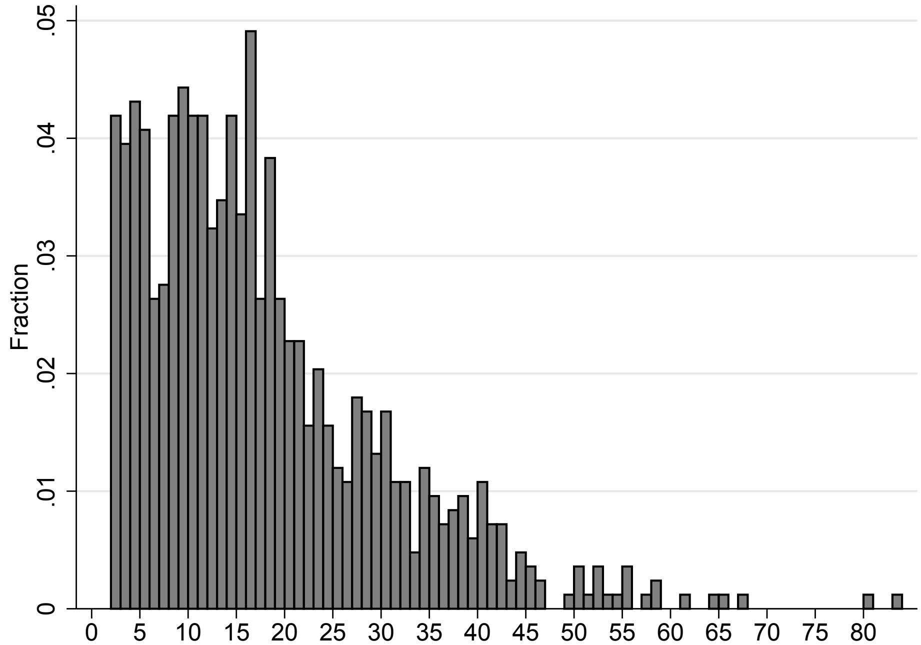
Panel A reports the share of African Americans born in AL, FL, GA, LA, MS, NC, and SC living outside of the former Confederate States. Panel B reports the share of whites born in KS, NE, ND, OK, and SD living outside of the Great Plains and border area shaded in light grey in Figure 2. For individuals born from 1891-1900, we measure their location using the 1900 Census. For individuals born from 1901-1910, we use the 1910 Census, and so forth. The shaded circles correspond to individuals born from 1916-1936, who comprise our sample from the Duke SSA/Medicare data. Source: IPUMS Census data, 1940-2000.

Figure A.2: Share Living Outside Birth Region, 1916-1936 Cohorts, by Age

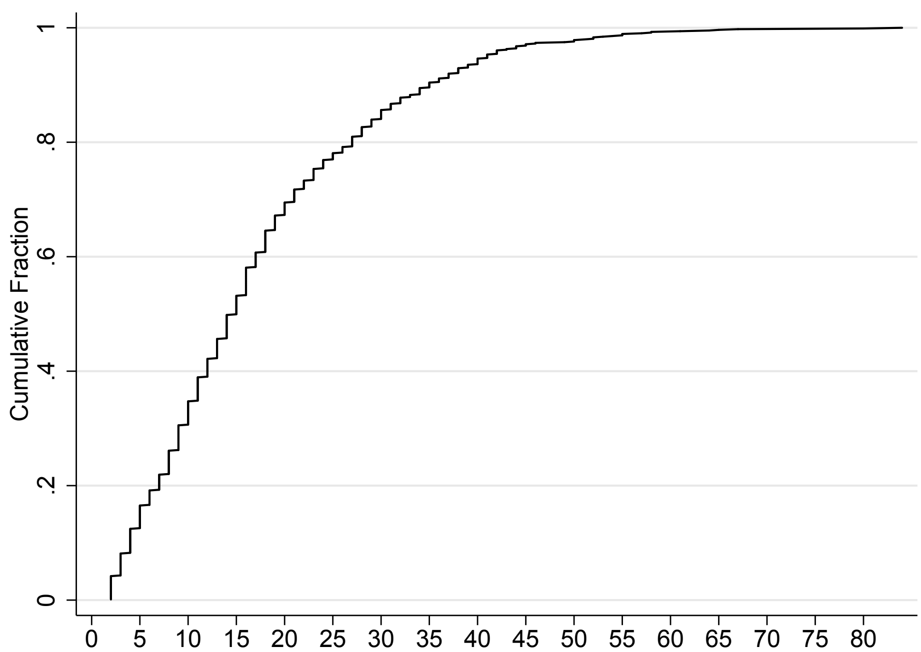


Notes: The solid line shows the percent of African Americans born from 1916-1936 in the seven Southern birth states we analyze (dark grey states in Figure 2a) living outside the South (light and dark grey states) at the time of Census enumeration. The dashed line shows the percent of whites born from 1916-1936 from the Great Plains states living outside the Great Plains or Border States. Both lines are locally mean-smoothed relationships of the underlying observations.
Source: Ruggles et al. (2010) data

Figure A.3: Number of Towns per Birth Town Group, Cross Validation, Black Moves out of South



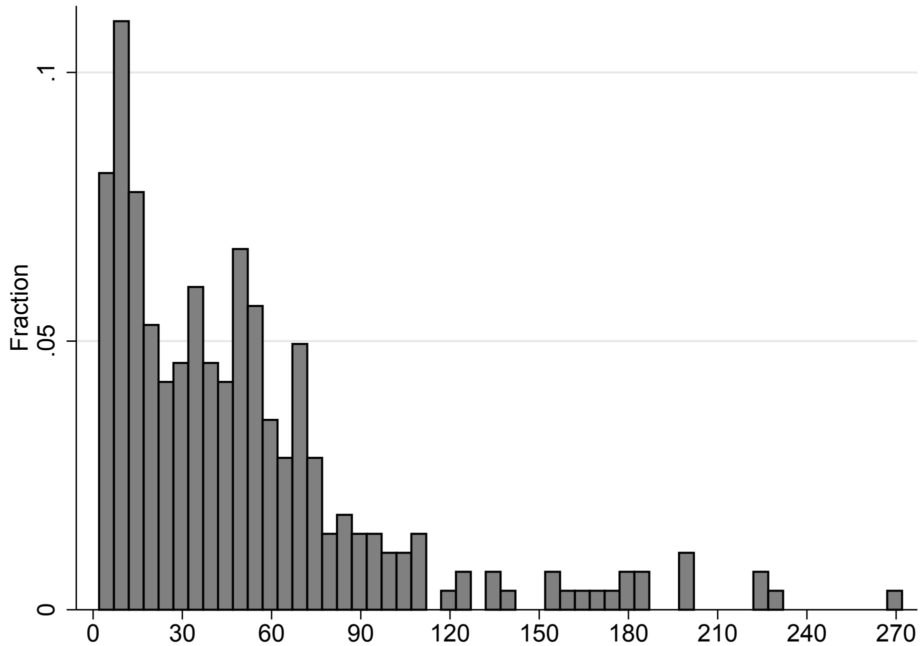
(a) Histogram



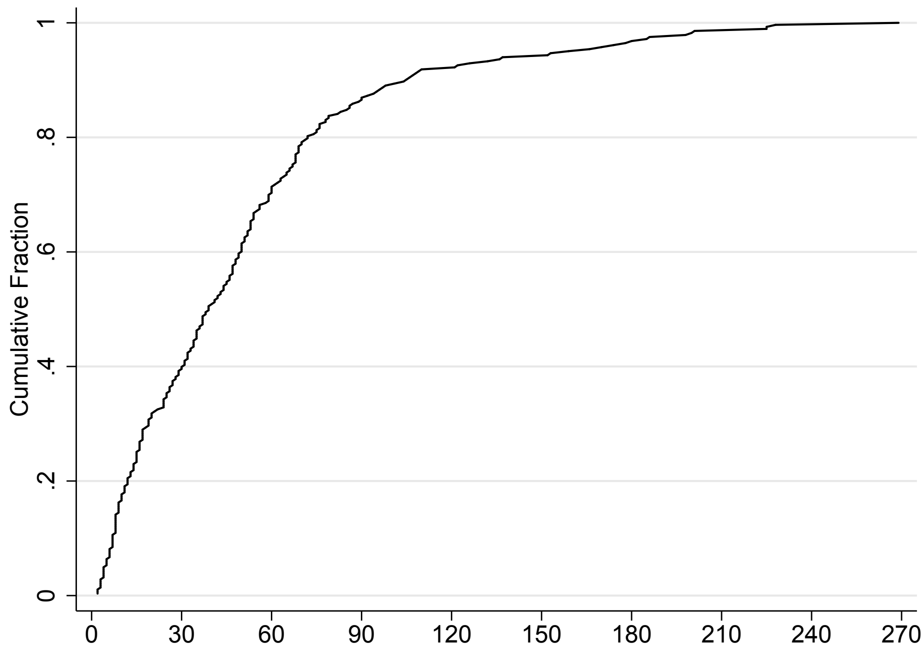
(b) Cumulative Distribution

Notes: Figure excludes groups with a single town, as these are not used in the analysis. Bin width in panel (a) is 1.
Source: Duke SSA/Medicare data

Figure A.4: Number of Towns per Birth Town Group, Cross Validation, White Moves out of Great Plains



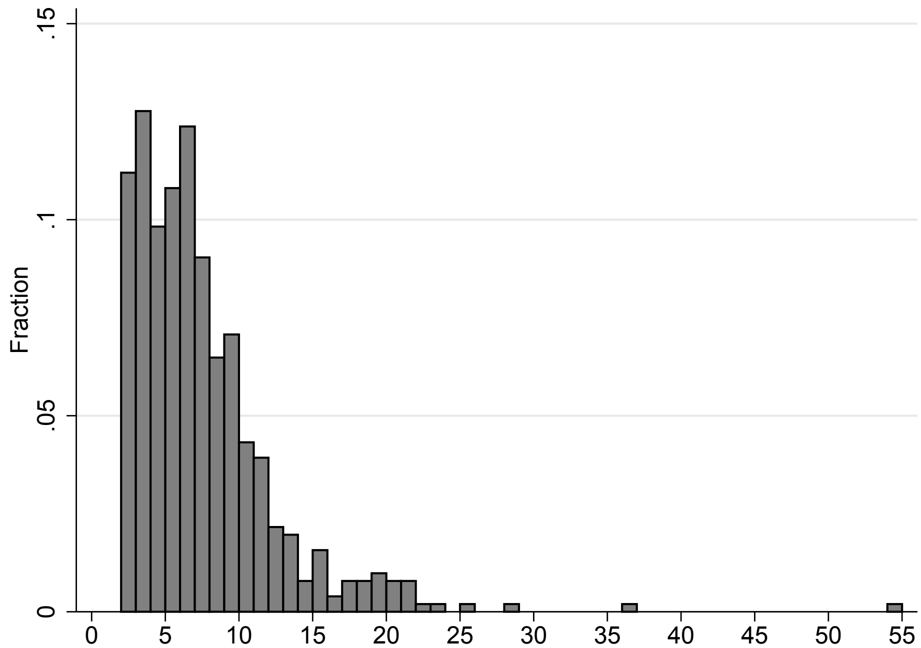
(a) Histogram



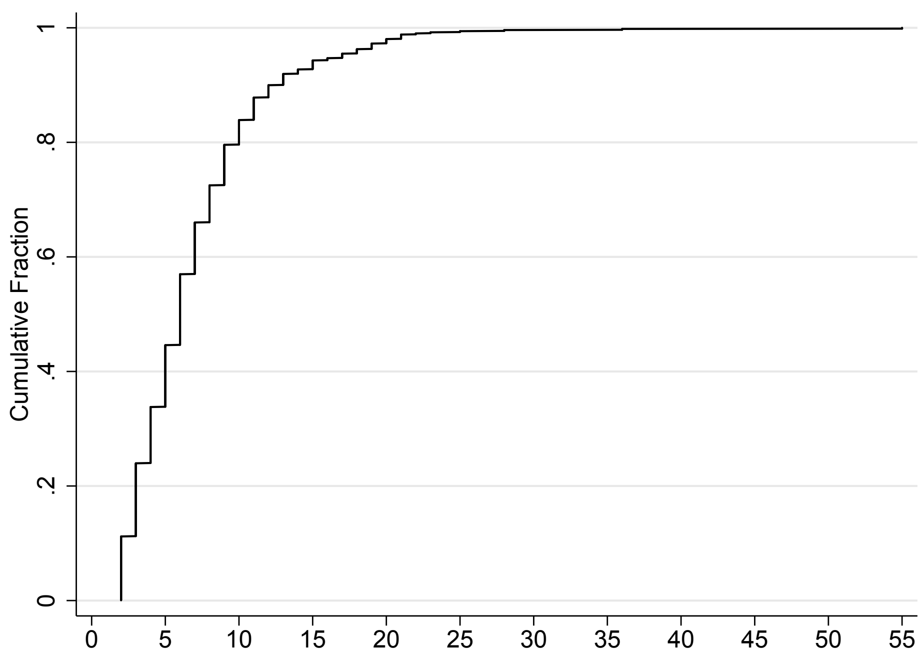
(b) Cumulative Distribution

Notes: Figure excludes groups with a single town, as these are not used in the analysis. Bin width in panel (a) is 5.
Source: Duke SSA/Medicare data

Figure A.5: Number of Towns per County, Black Moves out of South



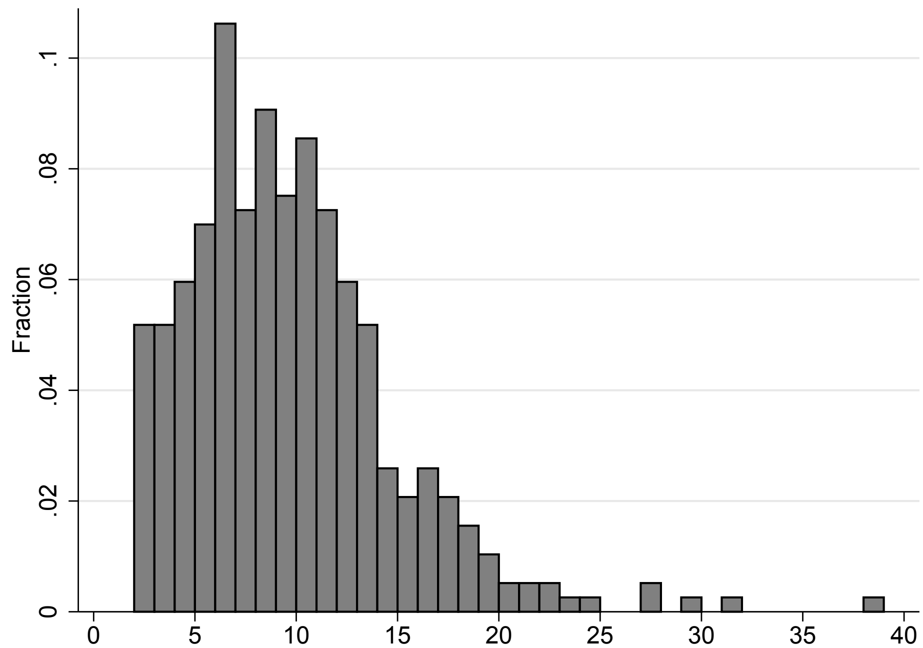
(a) Histogram



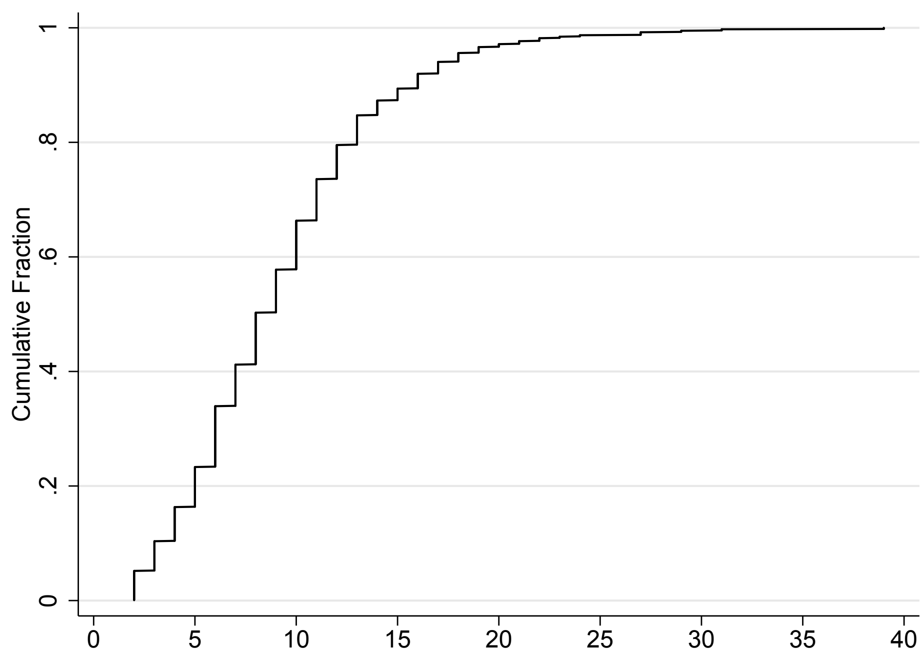
(b) Cumulative Distribution

Notes: Figure excludes groups with a single town, as these are not used in the analysis. Bin width in panel (a) is 1.
Source: Duke SSA/Medicare data

Figure A.6: Number of Towns per County, White Moves out of Great Plains



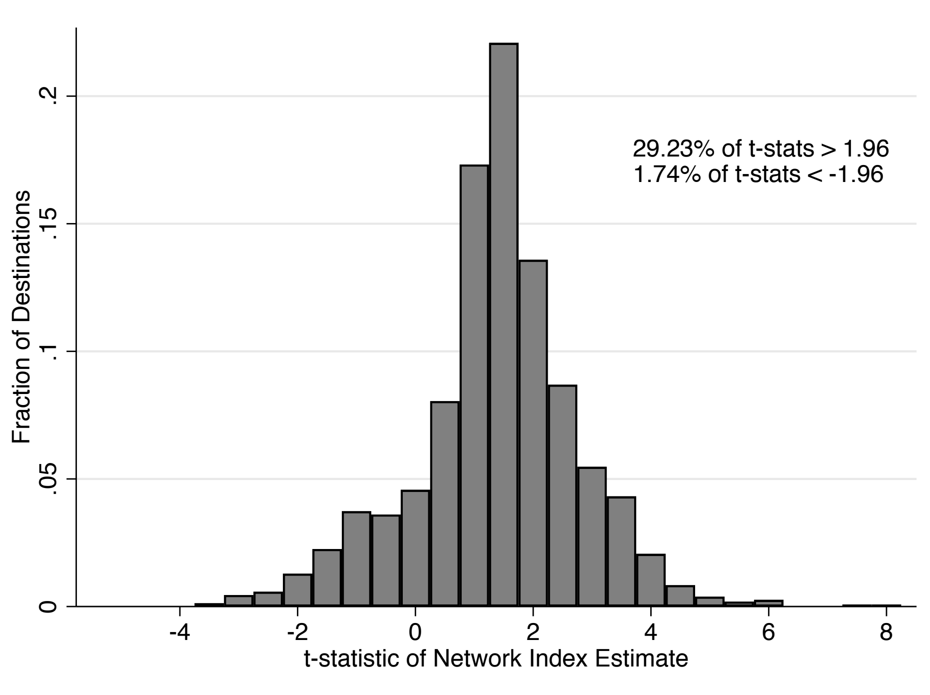
(a) Histogram



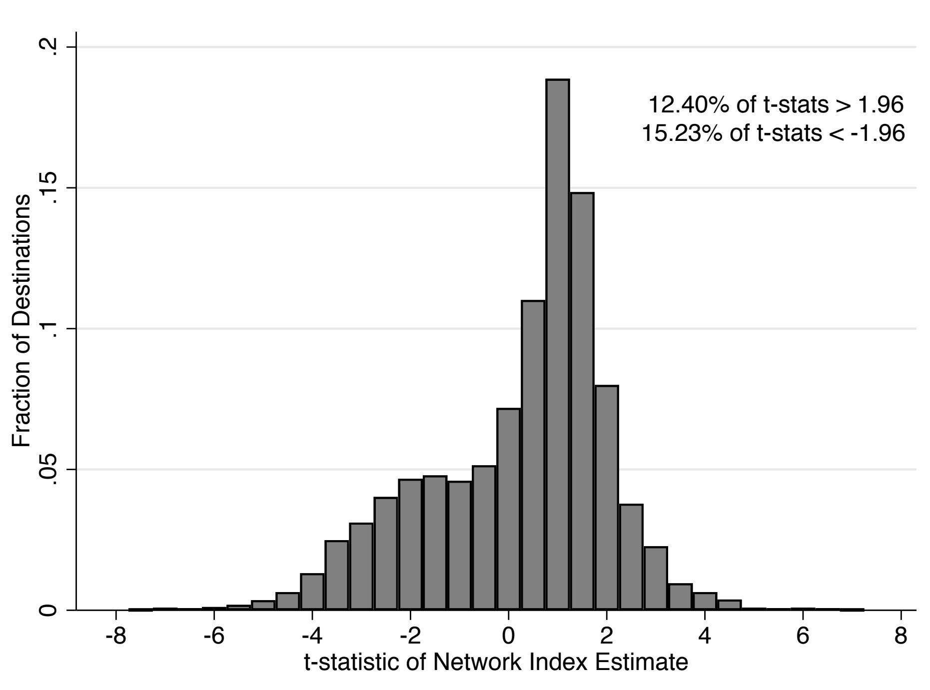
(b) Cumulative Distribution

Notes: Figure excludes groups with a single town, as these are not used in the analysis. Bin width in panel (a) is 1.
Source: Duke SSA/Medicare data

Figure A.7: Distribution of Destination-Level Network Index t-statistics



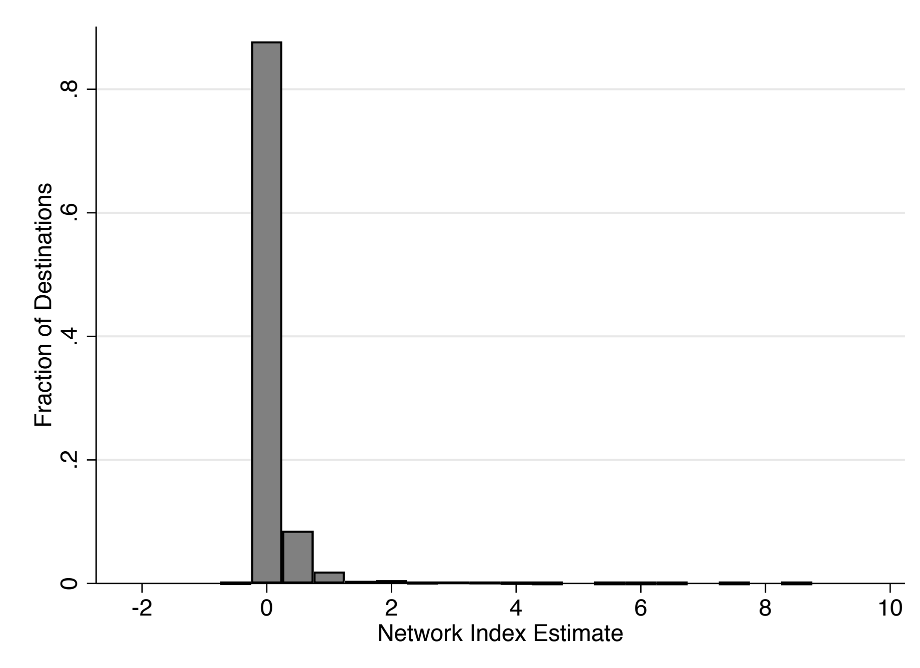
(a) Black Moves out of South



(b) White Moves out of Great Plains

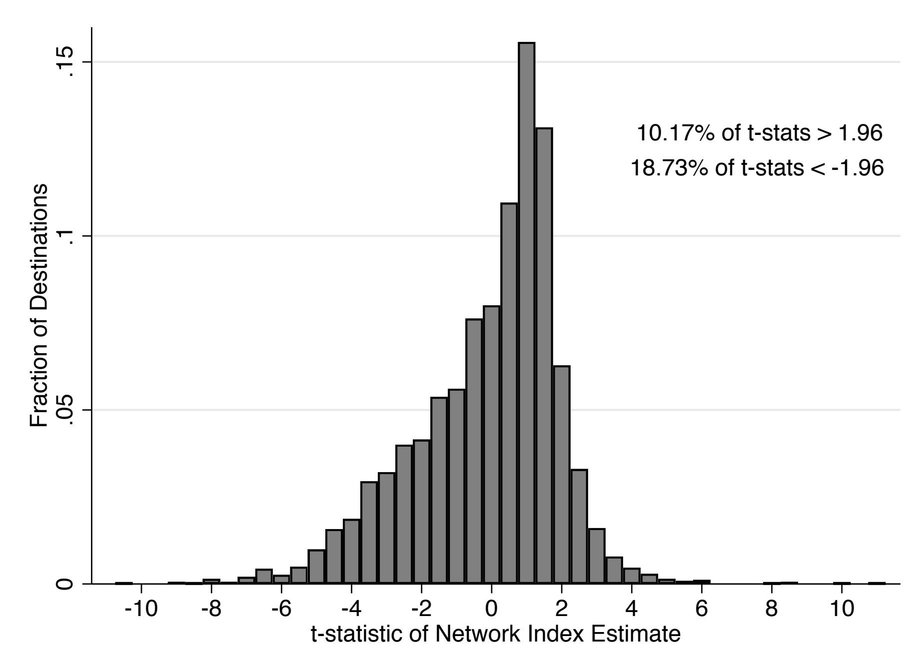
Notes: Bin width is 1/2. Birth town groups are defined by cross validation. Panel (a) omits the t-statistic of 13.7 from South Carolina to Hancock, WV.
Source: Duke SSA/Medicare data

Figure A.8: Distribution of Destination-Level Network Index Estimates, White Moves out of South



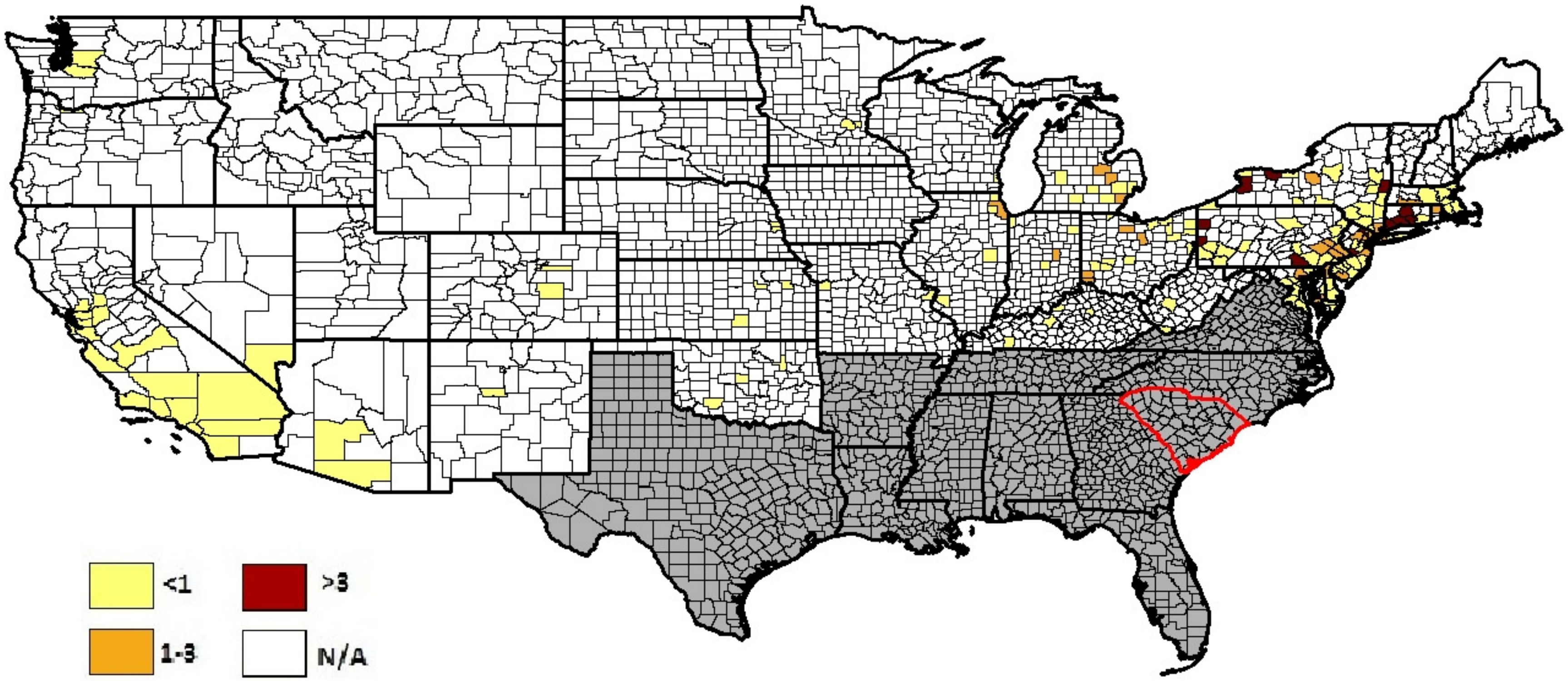
Notes: Bin width is 1/2. Figure omits estimate of $\hat{\Delta}_k = 19.3$ from Alabama to St. Joseph County, IN.
Source: Duke SSA/Medicare data

Figure A.9: Distribution of Destination-Level Network Index t-statistics, White Moves out of South



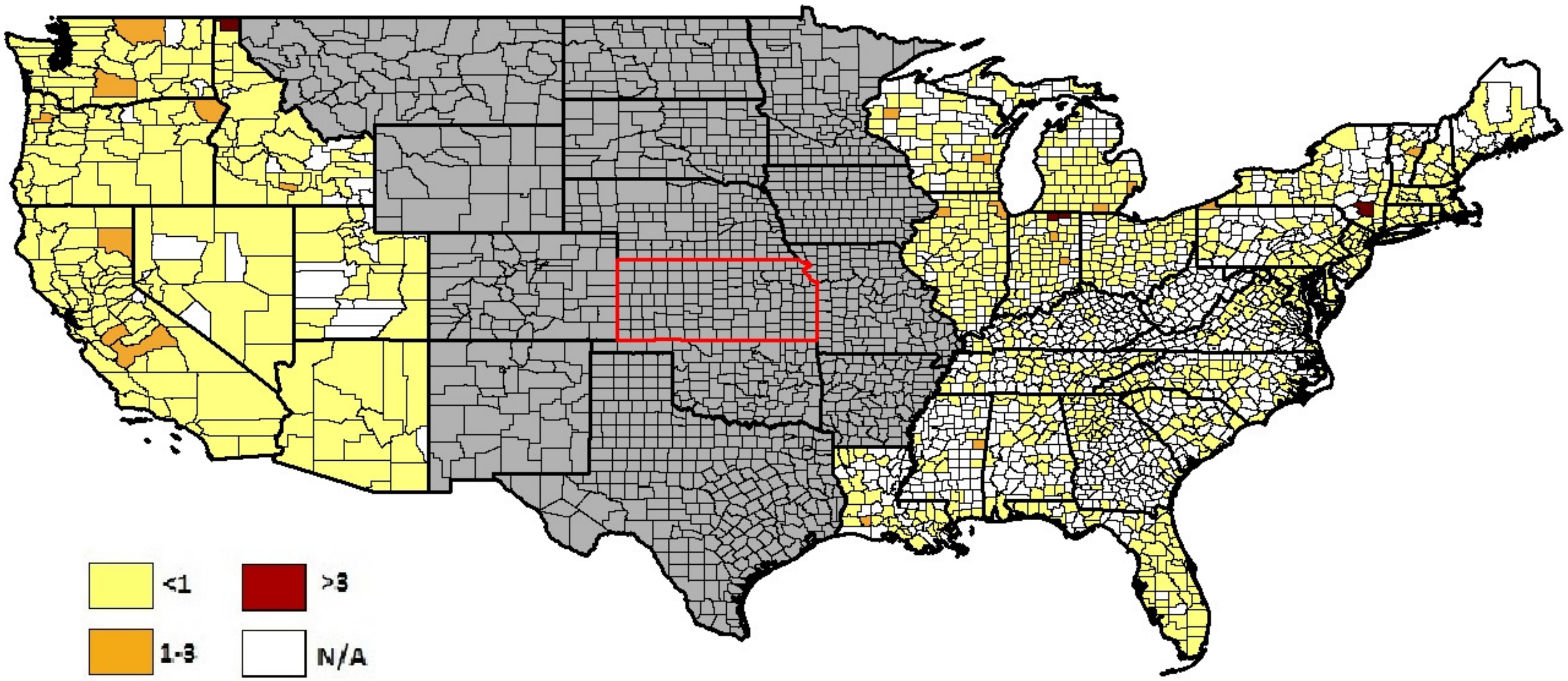
Note: Bin width is 1/2.
Source: Duke SSA/Medicare data

Figure A.10: Spatial Distribution of Destination-Level Network Index Estimates, South Carolina-born Blacks



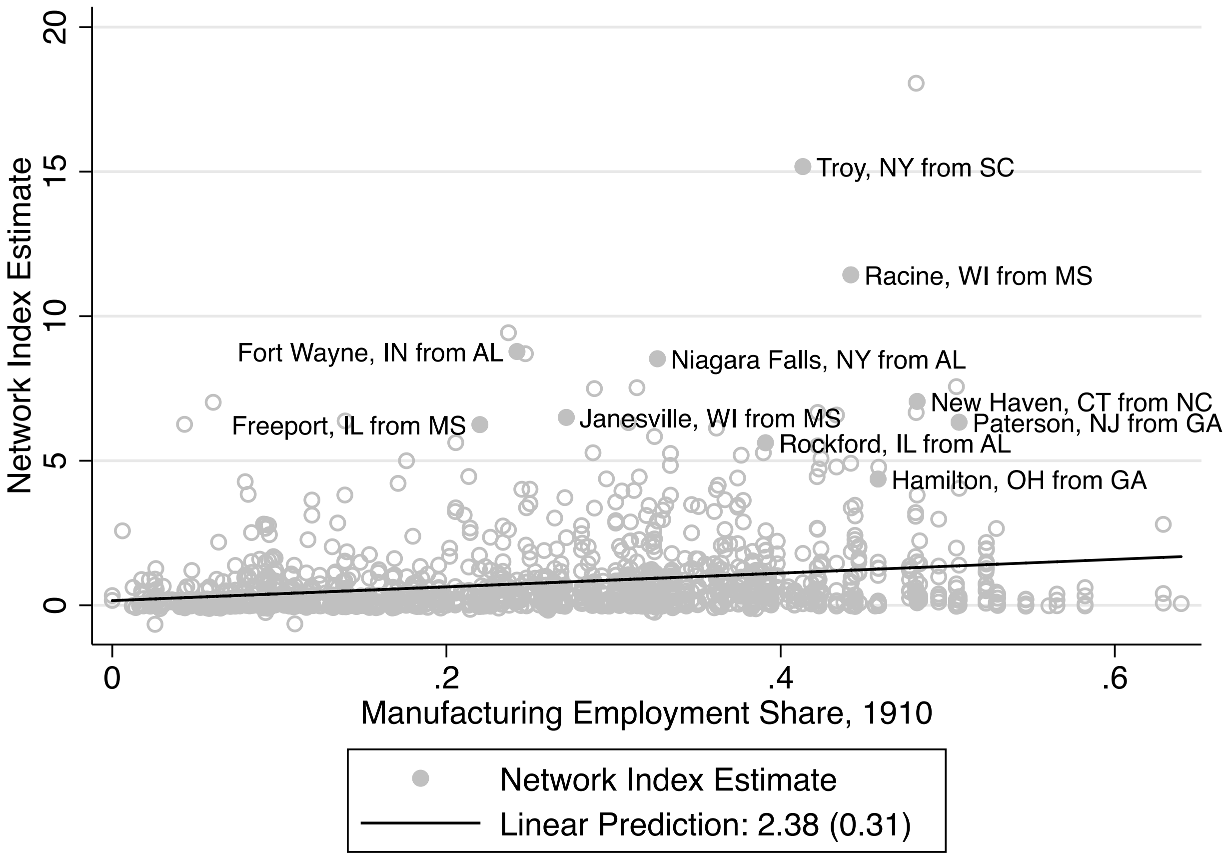
Notes: See note to Figure 4.

Figure A.11: Spatial Distribution of Destination-Level Network Index Estimates, Kansas-born Whites



Notes: See note to Figure 5.

Figure A.12: Relationship between Southern Black Destination-Level Network Index Estimates and 1910 Manufacturing Employment Share



Notes: Linear prediction comes from an OLS regression that includes a constant and 1910 manufacturing employment share. Listed are the cities in Table 2.
Sources: Duke SSA/Medicare data and Haines and ICPSR (2010) data