The Effect of Social Connectedness on Crime: Evidence from the Great Migration*

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Abstract

This paper estimates the effect of social connectedness on crime across U.S. cities from 1960-2009. Migration networks among African Americans from the South generated variation across destinations in the concentration of migrants from the same birth town. Using this novel source of variation, we find that social connectedness considerably reduces murders, robberies, assaults, burglaries, larcenies, and motor vehicle thefts, with a one standard deviation increase in social connectedness reducing murders by 13 percent and motor vehicle thefts by 9 percent. Our results appear to be driven by stronger relationships among older generations reducing crime committed by youth.

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1 Introduction

For almost 200 years, the enormous variance of crime rates across space has intrigued social scientists and policy makers (Guerry, 1833; Quetelet, 1835; Weisburd, Bruinsma and Bernasco, 2009). Standard covariates explain relatively little of the cross-city variation in crime, which suggests a potential role for social influences (Glaeser, Sacerdote and Scheinkman, 1996). One possible explanation is peer effects, whereby an individual is more likely to commit crime if his peers commit crime (e.g., Case and Katz, 1991; Glaeser, Sacerdote and Scheinkman, 1996; Damm and Dustmann, 2014). A non-rival explanation is that cities differ in the degree of social connectedness, or the strength of relationships between individuals, including those unlikely to commit crime.

There is widespread interest in the effects of social connectedness and the related concept of social capital. This interest partly stems from the possibility that relationships between individuals can address market failures and generate desirable outcomes that are difficult to accomplish with government policies. However, estimating the effects of social connectedness and social capital has proven challenging. Some of the most influential evidence comes from correlations between outcomes, such as income and crime, and proxies for social capital, like individuals' participation in community organizations, their stated willingness to intervene in the community, and their stated willingness to trust others (Sampson, Raudenbush and Earls, 1997; Putnam, 2000). These proxies for social capital reflect individuals' contemporaneous decision to invest in their community, which raises the concern that these correlations reflect reverse causality or omitted variables bias. As a result, the empirical importance of social capital continues to be debated (Durlauf, 2002).

This paper uses a new source of variation in social connectedness to estimate its effect on crime. Migration networks among millions of African Americans who moved out of the U.S. South from 1915-1970 generated variation across destinations in the concentration of migrants from the same birth town. For example, consider Beloit, Wisconsin and Middletown, Ohio, two cities similar along many dimensions, including the total number of Southern black migrants that moved there. Around 18 percent of Beloit's black migrants came from Pontotoc, Mississippi, while less than five percent of Middletown's migrants came from any single town. Historical accounts trace the sizable migration from Pontotoc to Beloit to a single influential migrant getting a job in 1914 at a manufacturer in search of workers. Furthermore, ethnographic and newspaper accounts suggest that Southern birth town networks translated into strong community ties in the North. Guided by a simple economic model, we proxy for social connectedness using a Herfindahl-Hirschman Index of birth town to destination city population flows for African Americans born in the South from 1916-1936, who we observe in the Duke SSA/Medicare dataset.

We estimate regressions that relate cross-city differences in crime from 1960-2009 to cross-city differences in social connectedness. Our main specification controls for the number of Southern black migrants that live in each city, to adjust for differences in the overall attractiveness of cities to black migrants, plus a rich set of demographic and economic variables and state-by-year fixed effects, to adjust for many potential determinants of crime. City-level crime counts come from FBI Uniform Crime Reports, which are widely available starting in 1960. We focus on social connectedness among black migrants because birth town migration networks are especially strong among this group (Stuart and Taylor, 2017) and qualitative and quantitative evidence supports our resulting empirical strategy.

We find that social connectedness leads to sizable reductions in crime rates. At the mean, a one standard deviation increase in social connectedness leads to a precisely estimated 13 percent decrease in murder, the best measured crime in FBI data. Our estimates imply that replacing Middletown's social connectedness with that of Beloit would decrease murders by 23 percent, robberies by 26 percent, and motor vehicle thefts by 16 percent. By comparison, the estimates in Chalfin and McCrary (2015) imply that a similar decrease in murders would require a 34 percent increase in the number of police officers. The elasticity of crime with respect to social connectedness ranges from -0.05 to -0.19 across the seven index crimes of murder, rape, robbery, assault, burglary, larceny, and motor vehicle theft, and is statistically distinguishable from zero for every crime besides rape.

A number of additional results clarify our main finding. Social connectedness reduces crimes that are more and less likely to have witnesses, which suggests that an increased probability of detection is not the only operative mechanism. The effect of social connectedness on crime does not appear to be driven by effects on employment, education, homeownership, the prevalence of single parents, or crack cocaine use. Other mechanisms, such as effects on norms, values, or skills, likely matter. Social connectedness especially reduces crimes committed by African American youth, who belong to the generations of migrants' children, grandchildren, and great-grandchildren. We also find that social connectedness reduces crimes committed by non-black individuals, consistent with cross-race peer effects or spillovers. The estimated effects decline over time, in line with the decline in the effective strength of our measure of social connectedness, as Southern black migrants aged and eventually died.

Several pieces of evidence support the validity of our empirical strategy. Historical accounts point to the importance of migrants who were well connected in their birth town and who worked for an employer in search of labor in establishing concentrated migration flows from Southern birth towns to Northern cities (Scott, 1920; Bell, 1933; Gottlieb, 1987; Grossman, 1989). Pioneer migrants, making initial location decisions in the 1910s, established the migration patterns that underlie subsequent variation in social connectedness. Consistent with a dominant role for such idiosyncratic factors, social connectedness is not correlated with crime rates from 1911-1916. We show that our results cannot be explained by migrants from the same birth town tending to move to cities with low unobserved determinants of crime and these unobserved factors persisting over time. Our results also are robust to controlling for the share of migrants in each destination that moved there because of their birth town migration network, a variable we estimate from a novel structural model of location decisions. Consequently, our estimates reflect the effect of social connectedness per se, as opposed to unobserved characteristics of certain migrants.

This paper contributes most directly to the literature studying how characteristics of social networks affect crime (Sampson, Raudenbush and Earls, 1997; Putnam, 2000). We also contribute to the literature in economics studying the impact of social capital and trust on various outcomes, including growth and development (Knack and Keefer, 1997; Miguel, Gertler and Levine, 2005), government efficiency and public good provision (La Porta et al., 1997; Alesina, Baqir and Easterly, 1999, 2000), financial development (Guiso, Sapienza and Zingales, 2004), and microfinance (Karlan, 2005, 2007; Cassar, Crowley and Wydick, 2007; Feigenberg, Field and Pande, 2013). Our primary contribution is new, more credible evidence on the effect of social connectedness on crime. We use variation in social connectedness that has the unusual and attractive property of being established decades before we measure outcomes as the result of a known process (birth town migration networks).[1] We also develop and parametrize a simple economic model that quantifies the potentially important role of peer effects in amplifying the effects of social connectedness on crime.

More broadly, there is enormous interest in the causes and consequences of criminal activity and incarceration in U.S. cities, especially for African Americans (Freeman, 1999; Neal and Rick, 2014; Evans, Garthwaite and Moore, 2016), and this paper demonstrates the importance of social connectedness in reducing crime. We also add to the literature on the consequences of the Great Migration for migrants and cities, which has not considered the effects of social connectedness before (e.g., Scroggs, 1917; Smith and Welch, 1989; Carrington, Detragiache and Vishwanath, 1996; Collins, 1997; Boustan, 2009, 2010; Hornbeck and Naidu, 2014; Black et al., 2015). This paper draws on Stuart and Taylor (2017), which examines the role of birth town migration networks among African Americans in more detail.

2 Historical Background on the Great Migration

The Great Migration saw nearly six million African Americans leave the South from 1910 to 1970 (Census, 1979).[2] Although migration was concentrated in certain destinations, like Chicago, Detroit, and New York, other cities also experienced dramatic changes. For example, Chicago's

[1] Social connectedness is a broader concept than social capital, trust, or collective efficacy. For example, social connectedness might reduce crime by increasing the probability that criminals are identified, and this behavior typically is not included in definitions of social capital, trust, or collective efficacy. At the same time, our measure might capture social capital that was transported from the South. Definitions of social capital vary, but Portes (1998) argues that a consensus definition is "the ability of actors to secure benefits by virtue of membership in social networks or other social structures" (p. 6). Fukuyama (1995), Putnam (2000), and Bowles and Gintis (2002) emphasize the role of trust and reciprocity in their definition of social capital. Karlan (2007) makes a similar distinction between social capital and social connections as we do.

[2] Parts of this section come from Stuart and Taylor (2017).

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 the 1970s.

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). Underlying causes included a less developed Southern economy, the decline in agricultural labor demand due to the boll weevil's destruction of 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: 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 their role diminished sharply after the 1920s, and most individuals paid for the relatively expensive train fares themselves (Gottlieb, 1987; Grossman, 1989).[3] African-American newspapers from the largest destinations circulated throughout the South, providing information on life in the North (Gottlieb, 1987; Grossman, 1989).[4]

Historical accounts and recent quantitative work indicate that birth town migration networks strongly affected location decisions during the Great Migration. Initial migrants, most of whom moved in the 1910s, chose their destination primarily in response to economic opportunity. Mi-

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

grants who worked for an employer in search of labor and were well connected in their birth town linked friends, family, and acquaintances to jobs and shelter in the North, sometimes leading to persistent migration flows from birth town to destination city (Rubin, 1960; Gottlieb, 1987). Describing this behavior shortly after the start of the Great Migration, Scott (1920) wrote,

> "The tendency was to continue along the first definite path. Each member of the vanguard controlled a small group of friends at home, if only the members of his immediate family. Letters sent back, representing that section of the North and giving directions concerning the route best known, easily influenced the next groups to join their friends rather than explore new fields. In fact, it is evident throughout the movement that the most congested points in the North when the migration reached its height, were those favorite cities to which the first group had gone" (p. 69).

In Stuart and Taylor (2017), we show that birth town migration networks strongly influenced the location decisions of African American migrants from the South.

The experience of John McCord captures many important features of early black migrants' location decisions.[5] 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 work 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 (Stuart and Taylor, 2017).[6]

Qualitative evidence documents the impact of social ties among African Americans from the same birth town on life in the North. For example, roughly 1,000 of Erie, Pennsylvania's 11,600

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

[6]This is 68 times larger than the percent of migrants from Mississippi that lived in Beloit's county at old age.

African American residents once lived in Laurel, Alabama, and almost half had family connections to Laurel, leading an Erie resident to say, "I'm surrounded by so many Laurelites here, it's like a second home" (Associated Press, 1983). Nearly forty percent of the migrants in Decatur, Illinois came from Brownsville, Tennessee, and Brownsville high school reunions took place in Decatur from the 1980s to 2000s (Laury, 1986; Smith, 2006).[7] As described by a Brownsville native, "Decatur's a little Brownsville, really" (Laury, 1986). Ethnographic work by Stack (1970) details the importance of birth town and family social ties among African Americans for childrearing and other behaviors. Motivated by these accounts, we now turn to a systematic analysis of the effect of social connectedness on crime.

3 A Simple Model of Crime and Social Connectedness

Social connectedness could reduce crime through multiple channels, such as promoting stronger norms, values, and skills or increasing the probability that criminals are identified and punished. In this section, we use a simple economic model to derive an empirical measure of social connectedness, and we show how the overall effect of social connectedness on crime depends on peer effects.

3.1 Individual Crime Rates

We focus on a single city and characterize individuals by their age and social ties. For simplicity, we consider a static model in which each younger individual makes a single decision about whether to commit crime, while older individuals do not commit crime. Each individual belongs to one of three groups: African Americans with ties to the South ($\tau = s$), African Americans without ties to the South ($\tau = n$), and all others ($\tau = w$). Older individuals have a tie to the South if they were born there. Younger individuals have a tie to the South if at least one parent, who is an older individual, was born in the South. We index younger individuals by i and older individuals by o.

[7] The 40 percent figure comes from the Duke SSA/Medicare dataset, described below.

For a younger individual who is black with ties to the South, we model the probability of committing crime as

$$\mathbb{E}[C_i|\tau_i = s, j_i = j] = \alpha^s + \beta^s\,\mathbb{E}[C_{-i}] + \sum_o \gamma^s_{i,o,j}, \tag{1}$$

where $C_i = 1$ if person i commits crime and $C_i = 0$ otherwise, and j_i denotes the birth town of i's parents. Equation (1) is a linear approximation to the optimal crime rule from a utility-maximizing model in which the relative payoff of committing crime depends on three factors. First, α^s, which is common to all individuals of type s, captures all non-social determinants of crime (e.g., due to the number of police or employment opportunities). Second, an individual's decision to commit crime depends on the expected crime rate among peers, $\mathbb{E}[C_{-i}]$. Finally, the effect of social connectedness is $\sum_o \gamma^s_{i,o,j}$, where $\gamma^s_{i,o,j}$ is the influence of older individual o on younger individual i. This reduced-form representation captures several possible channels through which social connectedness might affect crime. For example, older individuals might reduce crime among younger individuals by increasing younger individuals' stock of cognitive and non-cognitive skills, which boost earnings in the non-crime labor market (Heckman, Stixrud and Urzua, 2006), by promoting anti-crime norms and values (Stack, 1970), or by increasing the probability a criminal is identified and punished (Becker, 1968). Alternatively, social connectedness could increase crime by reinforcing unproductive norms or providing trust that facilitates criminal activity, as with the Ku Klux Klan, Mafia, or gangs (Fukuyama, 2000; Putnam, 2000). Ultimately, whether social connectedness decreases or increases crime is an empirical question.

Motivated by the qualitative evidence described in Section 2, we model social connectedness as a function of whether the parents of individual i share a birth town with individual o. In particular, $\gamma^s_{i,o,j} = \gamma^s_H$ if the individuals share a birth town connection, $j_i = j_o$, and $\gamma^s_{i,o,j} = \gamma^s_L$ otherwise. We assume that younger African Americans with ties to the South are only influenced by older African Americans with ties to the South, so that $\gamma^s_{i,o,j} = 0$ if $\tau_i \neq \tau_o$. Given these assumptions, the effect of social connectedness on person i is a weighted average of the high connectedness effect (γ^s_H)

and the low connectedness effect (γ_L^s),

$$\sum_o \gamma_{i,o,j}^s = \frac{N_{j,0}^s}{N_0^s}\gamma_H^s + \left(1 - \frac{N_{j,0}^s}{N_0^s}\right)\gamma_L^s, \tag{2}$$

where $N_{j,0}^s$ is the number of older individuals of type s from birth town j, and $N_0^s = \sum_j N_{j,0}^s$ is the total number of older individuals in the city. Because social interactions depend on birth town connections, the older generation's migration decisions lead to differences in expected crime rates for younger individuals with ties to different birth towns.

The Herfindahl-Hirschman Index emerges as a natural way to measure social connectedness in this model. In particular, the probability that a randomly chosen African American with ties to the South commits crime is

$$\mathbb{E}[C_i|\tau_i = s] = \alpha^s + \beta^s\,\mathbb{E}[C_{-i}] + \gamma_L^s + (\gamma_H^s - \gamma_L^s)\text{HHI}^s, \tag{3}$$

where $\text{HHI}^s \equiv \sum_j (N_{j,0}^s/N_0^s)^2$ is the Herfindahl-Hirschman Index of birth town to destination city population flows for African Americans from the South.[8] HHI^s approximately equals the probability that two randomly chosen members of the older generation share a birth town.[9] The direct effect of social connectedness on the type s crime rate is $\gamma_H^s - \gamma_L^s$. One reasonable case is $\gamma_H^s < \gamma_L^s < 0$, so that older individuals discourage younger individuals from committing crime, and the effect is stronger among individuals who share a birth town connection. Expressions analogous to equation (3) exist for African American youth without ties to the South ($\tau = n$) and non-black youth ($\tau = w$).

[8]In deriving equation (3), we assume that each Southern birth town accounts for the same share of individuals in the younger and older generations, so that $N_{j,0}^s/N_0^s = N_{j,1}^s/N_1^s \forall j$, where $N_{j,1}^s$ is the number of younger individuals of type s with a connection to birth town j, and $N_1^s = \sum_j N_{j,1}^s$ is the total number of younger individuals.

[9]The probability that two randomly chosen members of the older generation share a birth town is

$$\mathbb{P}[j_o = j_{o'}] = \sum_j \mathbb{P}[j_o = j_{o'}|j_{o'} = j]\,\mathbb{P}[j_{o'} = j] = \sum_j \left(\frac{N_{j,0}^s - 1}{N_0^s - 1}\right)\left(\frac{N_{j,0}^s}{N_0^s}\right) \approx \text{HHI}^s.$$

3.2 City-Level Crime Rates

In the equilibrium of this model, peer effects can magnify or diminish the effect of social connectedness on crime. We use HHI to measure social connectedness and allow peer effects to differ by the type of peer, leading to the following equilibrium,

$$\bar{C}^s = F^s(\alpha^s, \text{HHI}^s, \bar{C}^s, \bar{C}^n, \bar{C}^w) \tag{4}$$

$$\bar{C}^n = F^n(\alpha^n, \text{HHI}^n, \bar{C}^s, \bar{C}^n, \bar{C}^w) \tag{5}$$

$$\bar{C}^w = F^w(\alpha^w, \text{HHI}^w, \bar{C}^s, \bar{C}^n, \bar{C}^w), \tag{6}$$

where $\bar{C}^\tau$ is the crime rate among younger individuals of type τ, and F^τ characterizes the equilibrium crime rate responses. The equilibrium crime rate vector $(\bar{C}^s, \bar{C}^n, \bar{C}^w)$ is a fixed point of equations (4)-(6).

We are interested in the effect of social connectedness among African Americans with ties to the South, HHI^s, on equilibrium crime rates. Equations (4)-(6) imply that

$$\frac{d\bar{C}^s}{d\text{HHI}^s} = \frac{\partial F^s}{\partial \text{HHI}^s}\left(\frac{(1-J_{22})(1-J_{33})-J_{23}J_{32}}{\det(I-J)}\right) \equiv \frac{\partial F^s}{\partial \text{HHI}^s} m^s \tag{7}$$

$$\frac{d\bar{C}^n}{d\text{HHI}^s} = \frac{\partial F^s}{\partial \text{HHI}^s}\left(\frac{J_{23}J_{31}+J_{21}(1-J_{33})}{\det(I-J)}\right) \equiv \frac{\partial F^s}{\partial \text{HHI}^s} m^n \tag{8}$$

$$\frac{d\bar{C}^w}{d\text{HHI}^s} = \frac{\partial F^s}{\partial \text{HHI}^s}\left(\frac{J_{21}J_{32}+J_{31}(1-J_{22})}{\det(I-J)}\right) \equiv \frac{\partial F^s}{\partial \text{HHI}^s} m^w, \tag{9}$$

where I is the 3×3 identity matrix and J, a sub-matrix of the Jacobian of equations (4)-(6), captures the role of peer effects.[10] Equations (7)-(9) depend on the direct effect of HHI^s on crime among African Americans with ties to the South, $\partial F^s/\partial \text{HHI}^s$, and peer effect multipliers, m^s, m^n, and m^w. We assume the equilibrium is stable, which essentially means that peer effects are not too

[10] In particular,

$$J \equiv \begin{bmatrix} \partial F^s/\partial \bar{C}^s & \partial F^s/\partial \bar{C}^n & \partial F^s/\partial \bar{C}^w \\ \partial F^n/\partial \bar{C}^s & \partial F^n/\partial \bar{C}^n & \partial F^n/\partial \bar{C}^w \\ \partial F^w/\partial \bar{C}^s & \partial F^w/\partial \bar{C}^n & \partial F^w/\partial \bar{C}^w \end{bmatrix},$$

and J_{ab} is the (a, b) element of J. m^s is the $(1, 1)$ element of $(I - J)^{-1}$, m^n is the $(2, 1)$ element, and m^w is the $(3, 1)$ element.

large.[11] For example, if $J_{11} \equiv \partial F^s/\partial \bar{C}^s \geq 1$, and there are no cross-group peer effects, then a small increase in the crime rate among type s individuals leads to an equilibrium where all type s individuals commit crime. In a stable equilibrium, a small change in any group's crime rate does not lead to a corner solution.

Our main theoretical result is that if social connectedness reduces the crime rate of African Americans with ties to the South, then social connectedness reduces the crime rate of all groups, as long as the equilibrium is stable and peer effects (i.e., elements of J) are non-negative.

Proposition 1. *$d\bar{C}^s/dHHI^s \leq 0, d\bar{C}^n/dHHI^s \leq 0$, and $d\bar{C}^w/dHHI^s \leq 0$ if $\partial F^s/\partial HHI^s < 0$, the equilibrium is stable, and peer effects are non-negative.*

In a stable equilibrium with non-negative peer effects, the crime-reducing effect of social connectedness among Southern African Americans is not counteracted by higher crime rates among other groups. Hence, equilibrium crime rates of all groups weakly decrease in Southern black social connectedness. With negative cross-group peer effects, the reduction in crime rates among Southern African Americans could lead to higher crime by other groups. A symmetric result holds if social connectedness instead increases the crime rate of African Americans with ties to the South. Proposition 1 is not surprising, and we provide a proof in Appendix A.

Because of data limitations, most of our empirical analysis examines the city-level crime rate, $\bar{C}$, which is a weighted average of the three group-specific crime rates,

$$\bar{C} = P^b[P^{s|b}\bar{C}^s + (1 - P^{s|b})\bar{C}^n] + (1 - P^b)\bar{C}^w, \tag{10}$$

where P^b is the black population share and $P^{s|b}$ is the share of the black population with ties to the South. Proposition 1 provides sufficient, but not necessary, conditions to ensure that Southern black social connectedness decreases the city-level crime rate, $\bar{C}$, when the direct effect is negative. There exist situations in which cross-group peer effects are negative, but an increase in HHI^s

[11]The technical assumption underlying stability is that the spectral radius of J is less than one. This condition is analogous to the requirement in linear-in-means models that the slope coefficient on the endogenous peer effect is less than one in absolute value (e.g., Manski, 1993).

still decreases the city-level crime rate. Guided by this theoretical analysis, we next describe our empirical strategy for estimating the effect of social connectedness on crime.

4 Data and Empirical Strategy

4.1 Data on Crime, Social Connectedness, and Control Variables

To estimate the effect of social connectedness on crime, we use three different data sets. We measure annual city-level crime counts using FBI Uniform Crime Report (UCR) data for 1960-2009, available from ICPSR. UCR data contain voluntary monthly reports on the number of offenses reported to police, which we aggregate to the city-year level.[12] We focus on the seven commonly studied index crimes: murder and non-negligent manslaughter ("murder"), forcible rape ("rape"), robbery, assault, burglary, larceny, and motor vehicle theft. Murder is the best measured crime, and robbery and motor vehicle theft are also relatively well-measured (Blumstein, 2000; Tibbetts, 2012). Missing crimes are indistinguishable from true zeros in the UCR. Because cities in our sample almost certainly experience property crime each year, we drop all city-years in which any of the three property crimes (burglary, larceny, and motor vehicle theft) equal zero.[13] We also use annual population estimates from the Census Bureau in the UCR data.

The Duke SSA/Medicare dataset provides the birth town to destination city population flows that underlie our measure of social connectedness. The data contain sex, race, date of birth, date of death (if deceased), and the ZIP code of residence at old age (death or 2001, whichever is earlier) for over 70 million individuals who received Medicare Part B from 1976-2001. In addition, the data include a 12-character string with self-reported birth town information from the Social Security Administration NUMIDENT file, which is matched to places, as described in Black et al. (2015). These data capture long-run location decisions, as we only observe individuals' location at birth

[12] We use Federal Information Processing System (FIPS) place definitions of cities. We follow Chalfin and McCrary (2015) in decreasing the number of murders for year 2001 in New York City by 2,753, the number of victims of the September 11 terrorist attack.

[13] Out of 21,183 city-years in the data, at least one of the three property crimes equals zero for 956 city-years (4.5 percent).

and old age.[14] As a result, our measure of social connectedness for each city does not vary over time. We focus on individuals born from 1916-1936 in the former Confederate states, which we refer to as the South. Out-migration rates for the 1916-1936 cohorts are among the highest of all cohorts in the Great Migration (Appendix Figure A.1), and coverage rates in the Duke data decline considerably for earlier and later cohorts (Black et al., 2015). We restrict our main analysis sample to cities with at least 25 Southern-born African American migrants in the Duke dataset to improve the reliability of our estimates.

Census city data books provide numerous covariates for 1960, 1970, 1980, 1990, and 2000. These data are only available for cities with at least 25,000 residents in 1960, 1980, and 1990, and we apply the same restriction for 1970 and 2000. We limit our sample to cities in the Northeast, Midwest, and West Census regions to focus on the cross-region moves that characterize the Great Migration. Our main analysis sample excludes cities with especially severe measurement errors in the crime data, as described in Appendix B. Appendix Tables A.1 and A.2 provide summary statistics.

4.2 Estimating the Effect of Social Connectedness on Crime

Our main estimating equation is

$$Y_{k,t} = \exp[\ln(\text{HHI}_k)\delta + \ln(N_k)\theta + X'_{k,t}\beta] + \epsilon_{k,t}, \tag{11}$$

where $Y_{k,t}$ is the number of crimes in city k in year t. The key variable of interest is our proxy for social connectedness among African Americans with ties to the South, $\text{HHI}_k = \sum_j (N_{j,k}/N_k)^2$, where $N_{j,k}$ is the number of migrants from birth town j that live in destination city k, and $N_k \equiv \sum_j N_{j,k}$ is the total number of migrants. A Herfindahl-Hirschman Index is a natural way to measure social connectedness, as shown in Section 3. $X_{k,t}$ is a vector of covariates, including log pop-

[14] As described in detail below, there was relatively little migration for our sample after leaving the South, so our ability to observe individuals' location only in old age is not particularly important.

ulation and other variables described below, and $\epsilon_{k,t}$ captures unobserved determinants of crime.[15] We use an exponential function in equation (11) because there are no murders for many city-year observations (Appendix Table A.1).[16]

Our proxy for social connectedness varies only across cities, but the number of crimes varies across both cities and years. Instead of collapsing the data into city-level observations, we use equation (11) to more flexibly control for the covariates in $X_{k,t}$ and because our panel of cities is not balanced. We cluster standard errors by city to allow for arbitrary autocorrelation in the unobserved determinants of crime. As a result, the number of cities is most relevant for thinking about the number of observations in our regressions.

The key parameter of interest is δ, which we interpret as the elasticity of the crime *rate* with respect to HHI_k, because we control for log population and specify the conditional mean as an exponential function. If social connectedness reduces the city-level crime rate, then $\delta < 0$. We estimate δ using cross-city variation in social connectedness, conditional on the total number of migrants and other covariates. To identify δ, we make the following conditional independence assumption,

$$\epsilon_{k,t} \perp\!\!\!\perp \text{HHI}_k | (N_k, X_{k,t}). \tag{12}$$

Condition (12) states that, conditional on the number of migrants living in city k and the vector of control variables, social connectedness is independent of unobserved determinants of crime from 1960-2009. This condition allows the total number of migrants, N_k, to depend arbitrarily on unobserved determinants of crime, $\epsilon_{k,t}$.[17]

We include several control variables in $X_{k,t}$ that bolster the credibility of condition (12). State-

[15]Because equation (11) includes $\ln(\text{HHI}_k)$, $\ln(N_k)$, and log population, our estimate of δ would be identical if we instead used city population as the denominator of HHI_k.

[16]We estimate the parameters in equation (11) using a Poisson quasi-maximum likelihood estimator. Consistent estimation of (δ, θ, β) requires the assumption that $E[Y_{k,t}|\cdot] = \exp[\ln(\text{HHI}_k)\delta + \ln(N_k)\theta + X'_{k,t}\beta]$, but does not require any restriction on the conditional variance of the error term (Wooldridge, 2002). Given this, we use the representation in equation (11) to facilitate discussion of our assumptions about unobserved determinants of crime.

[17]Condition (12) does not guarantee identification of the other parameters in equation (11) besides δ. For example, identification of θ requires exogenous variation in the total number of migrants in each city. Boustan (2010) provides one possible strategy for identifying θ, but we do not pursue that here.

by-year fixed effects flexibly account for determinants of crime that vary over time at the state level, due to changes in economic conditions, police enforcement, government spending, and other factors. Demographic covariates include log population, percent black, percent female, percent age 5-17, percent age 18-64, percent age 65 and older, percent at least 25 years old with a high school degree, percent at least 25 years old with a college degree, and log city area. Economic covariates include log median family income, unemployment rate, labor force participation rate, and manufacturing employment share.[18] Because social connectedness could affect some of these covariates, we examine the sensitivity of our results to excluding them. We have log population estimates for every year and, with a few exceptions, we observe the remaining demographic and economic covariates every ten years from 1960-2000.[19] In explaining crime in year t, we use covariates corresponding to the decade in which t lies. We allow coefficients for all covariates in $X_{k,t}$ to vary across decades to account for possible changes in the importance of economic and demographic variables.

Several pieces of evidence support the validity of condition (12). First, variation in social connectedness stems from location decisions made over 40 years before we estimate effects on crime. As described in Section 2, pioneer migrants in the 1910s chose their destination in response to economic opportunity, and idiosyncratic factors, like a migrant's ability to persuade friends and family to join them, strongly influenced whether other migrants followed. Nonetheless, some of the variation in social connectedness could stem from city characteristics, such as the manufacturing employment share, that affect crime from 1960-2009. We include many variables in $X_{k,t}$ to address this concern. Furthermore, as described in Appendix C, observed economic and demographic variables explain little of the cross-city variation in social connectedness. Importantly, we also control for the log number of Southern black migrants that live in each city, to adjust for differences in the attractiveness of cities to these migrants.

[18] Stuart and Taylor (2017) find that the manufacturing employment share is associated with stronger flows of birth town migration networks among Southern black migrants.

[19] The exceptions are percent female (not observed in 1960), percent with a high school degree and a college degree (not observed in 2000), log median family income (not observed in 2000), and manufacturing share (not observed in 2000). For decades in which a covariate is not available, we use the adjacent decade.

Table 1 provides further support for our empirical strategy, showing that social connectedness is not correlated with murder rates from 1911-1916. In particular, we regress $\ln(\text{HHI}_k)$ on $\ln(N_k)$ and log murder rates from 1911-1916, measured using historical mortality statistics for cities with at least 100,000 residents in 1920 (Census, 1922). We find no statistically or substantively significant relationship between social connectedness and early century murder rates, and this conclusion holds when we use inverse probability weights to make this sample of cities more comparable to our main analysis sample on the demographic and economic covariates listed above.[20] These results partially dismiss the possibility that social connectedness is correlated with extremely persistent unobserved determinants of crime, which could threaten our empirical strategy.

If anything, limitations in the data used to construct HHI_k could lead us to understate any negative effect of social connectedness on crime. We construct HHI_k and N_k using migrants' location at old age, measured from 1976-2001. In principle, migration after 1960, when we first measure crime, could influence HHI_k and the estimated effect on crime, δ. If migrants with a higher concentration of friends and family nearby were less likely to out-migrate in response to higher crime shocks, $\epsilon_{k,t}$, then HHI_k would be larger in cities with greater unobserved determinants of crime. This would bias our estimate of δ upwards, making it more difficult to conclude that social connectedness reduces crime. Reassuringly, Table 2 reveals very low migration rates among African Americans who were born in the South from 1916-1936 and living in the North, Midwest, and West. Around 90 percent of individuals stayed in the same county for the five-year periods from 1955-1960, 1965-1970, 1975-1980, 1985-1990, and 1995-2000. This suggests that our inability to construct HHI_k using migrants' location before 1960 is relatively unimportant.

Figure 1 shows that social connectedness stems largely from a single sending town's migrants. Sixty-six percent of the variation in log HHI is explained by the leading term of log HHI, which equals the log squared share of migrants from the top sending town. This finding reinforces the importance of idiosyncratic features of migrants and birth towns in generating variation in social

[20] We do not adjust the standard errors in columns 3-4 for the use of inverse probability weights. As a result, the p-values for these columns are likely too small, which further reinforces our finding of no statistically significant relationship. Appendix Table A.3 compares the observed characteristics of cities for which we do and do not observe 1911-1916 murder rates.

connectedness.[21]

5 The Effect of Social Connectedness on Crime

5.1 Main Results

Table 3 shows that social connectedness leads to sizable and statistically significant reductions in murder, robbery, assault, burglary, larceny, and motor vehicle theft. The table reports estimates of equation (11) for an unbalanced panel of 479 cities.[22] As seen in column 1, the estimated elasticity of the murder rate with respect to HHI is -0.161 (0.040). The estimates for robbery and motor vehicle theft, two other well-measured crimes in the FBI data, are -0.186 (0.034) and -0.114 (0.045). At the mean, these estimates imply that a one standard deviation increase in social connectedness leads to a 13 percent decrease in murders, a 15 percent decrease in robberies, and a 9 percent decrease in motor vehicle thefts. Summed over the 50 years from 1960-2009, a one standard deviation increase in social connectedness leads to 43 fewer murders, 1,612 fewer robberies, and 2,679 fewer motor vehicle thefts per 100,000 residents.

Simple examples help further illustrate the sizable effects of social connectedness on crime. First, consider Middletown, Ohio and Beloit, Wisconsin. These cities are similar in their total number of Southern black migrants, 1980 population, and 1980 black population share, but Beloit's HHI is over four times as large as Middletown's (0.057 versus 0.014).[23] The estimates in Table 3 imply that replacing Middletown's HHI with that of Beloit would decrease murders by 23 percent, robberies by 26 percent, and motor vehicle thefts by 16 percent. By comparison, the estimates in

[21] Appendix Table A.4 displays the relationship between log HHI and estimates of social capital, based mainly on 1990 county-level data, from Rupasingha, Goetz and Freshwater (2006). The social capital estimates depend on the density of membership organizations, voter turnout for presidential elections, response rates for the decennial Census, and the number of non-profit organizations. Correlations between log HHI and various measures of social capital are positive, but small and mostly indistinguishable from zero. Weak correlations are not particularly surprising, given the different time periods involved and the fact that these social capital estimates do not isolate social ties among African Americans. Consistent with the latter consideration, correlations are somewhat larger when we focus on cities with an above median black population share.

[22] Appendix Table A.7 displays results for all covariates in the regressions.

[23] For Middletown and Beloit, the number of Southern black migrants is 376 and 407; the 1980 population is 35,207 and 43,719; and the 1980 percent black is 11.3 and 12.0.

Chalfin and McCrary (2015) imply that a similar decrease in murders would require a 34 percent increase in the number of police officers.[24] The effect of social connectedness is even larger in other examples. HHI in Decatur, Illinois is almost twenty times larger than that of Albany, NY (0.118 versus 0.006).[25] Replacing Albany's HHI with that of Decatur would decrease murders by 48 percent, robberies by 55 percent, and motor vehicle thefts by 34 percent. While these effects are sizable, they are reasonable in light of the tremendous variation in crime rates across cities (Appendix Table A.2).

5.2 Robustness and Threats to Empirical Strategy

Table 4 demonstrates that our results are robust to various sets of control variables. We focus on the effect of social connectedness on murder, given its importance for welfare and higher measurement quality. Column 1 repeats our baseline specification to facilitate comparisons.[26] Estimates are very similar when excluding demographic or economic covariates (columns 2-3), when replacing $\ln(N_k)$ with ten indicator variables to control flexibly for the number of Southern black migrants (column 4), and when controlling for log HHI and the log number of Southern white migrants and foreign immigrants (column 5).[27] Column 6 shows that our results also are similar when controlling for racial fragmentation, which could affect the formation of social capital (Alesina and Ferrara, 2000), and the Hispanic population share.[28]

One possible concern is that our results reflect the effect of characteristics of migrants' birth place, as opposed to social connectedness. To examine this, we construct migrant-weighted aver-

[24]Chalfin and McCrary (2015) estimate an elasticity of murder with respect to police of -0.67, over four times the size of our estimated elasticity of murder with respect to social connectedness.

[25]For Decatur and Albany, the number of Southern black migrants is 760 and 874; the 1980 population is 94,081 and 101,727; and the 1980 percent black is 14.6 and 15.9.

[26]The sample in Table 4 differs slightly from that in Table 3 because some of the additional covariates that we consider are missing for nine cities.

[27]We use country of birth to construct HHI for immigrants. The coefficient on log HHI is -0.105 (0.041) for immigrants and 0.027 (0.044) for Southern whites. We emphasize the results for Southern black migrants because previous work documents the importance of birth town migration networks for African Americans (Stuart and Taylor, 2017), we are most confident in the validity of condition (12) for this group, and we are most confident in the interpretation of HHI as reflecting social connectedness for this group.

[28]Following Alesina and Ferrara (2000), we define racial fragmentation as one minus an HHI of the share of population that is white, black, American Indian, and any other race. We use the 1970 values for 1960 because these data are not available.

ages of Southern birth county characteristics. In particular, we use the 1920 Census to measure the black farm ownership rate, black literacy rate, black population density, percent black, and percent rural. We also measure exposure to Rosenwald schools, which increased educational attainment among African Americans in the South (Aaronson and Mazumder, 2011). As seen in column 7, our results are extremely similar when adding these controls.

A related concern is that our results reflect the effect of unobserved characteristics of migrants who chose the same destination as other migrants from their birth town. Census data reveal that Southern black migrants living in a state or metropolitan area with a higher share of migrants from their birth state have less education and income (Appendix Table A.8).[29] As a result, migrants who followed their birth town network likely had less education and earnings capacity than other migrants. This negative selection on education and earnings could generate a positive correlation between HHI_k and $\epsilon_{k,t}$, making it more difficult to find a negative effect of social connectedness on crime. At the same time, migrants who followed their birth town network might display greater cooperation or other "pro-social" behaviors. To address this possibility, we estimate a structural model of location decisions, described in Appendix D, which allows us to estimate the share of migrants in each destination that moved there because of their birth town migration network. When used as a covariate in equation (11), this variable proxies for unobserved characteristics of migrants that chose to follow other migrants from their birth town. Column 8 of Table 4 shows that the estimated effect of social connectedness on murder barely changes when we control for the share of migrants that chose their destination because of their birth town migration network.[30] Consequently, our results appear to reflect the effect of social connectedness per se, as opposed to unobserved characteristics of certain migrants.

Although Table 4 addresses many potential concerns, it is possible that cities with higher social connectedness had lower unobserved determinants of crime, $\epsilon_{k,t}$, for some other reason. For example, if connected groups of migrants moved to cities with low crime rates, and unobserved

[29]Research on immigrants in the U.S. finds similar patterns of selection (Bartel, 1989; Bauer, Epstein and Gang, 2005; McKenzie and Rapoport, 2010).

[30]Results are nearly identical when we use quadratic, cubic, or quartic functions of this variable (not reported).

determinants of crime persisted over time, then our estimate of δ could be biased downwards. We have already presented some evidence against this threat by showing that log HHI is not correlated with homicide rates from 1911-1916 (Table 1). To provide more direct evidence against this threat, we estimate the effect of social connectedness on crime for each five-year interval from 1965-2009 while controlling for deciles of the average crime rate from 1960-1964. If our results were driven entirely by connected groups of migrants initially sorting into cities with low crime rates and unobserved determinants of crime persisting over time, then controlling for the 1960-1964 crime rate would eliminate any correlation between social connectedness and crime rates in later years. On the other hand, if connected groups of migrants did not sort into cities on the basis of crime rates and condition (12) is valid, then controlling for the 1960-1964 crime rate will not completely attenuate the estimate of δ; adding this control could partially attenuate estimates because unobserved determinants of crime are serially correlated, but this attenuation should diminish with time. We do not control for the 1960-1964 crime rate in our main specification, as this leads to a biased estimate of δ. However, to the extent that this control does not entirely eliminate the relationship between crime and HHI, this approach rules out a potential threat to our empirical strategy.

Panel A of Figure 2 shows that the effect of social connectedness on murder is nearly identical when controlling for the 1960-1964 murder rate. This similarity arises from the relatively weak effect of social connectedness on murders from 1960-1964. Panel B shows that controlling for 1960-1964 motor vehicle thefts attenuates the estimated effects of social connectedness from 1965-1979, but negligibly so for 1980-forward. This result stems from a sizable effect of social connectedness on motor vehicle thefts from 1960-1964 and a positive serial correlation of crime rates. Reassuringly, both panels are inconsistent with connected groups of migrants initially sorting into cities with low crime rates and unobserved determinants of crime persisting over time. As a result, Figure 2 provides support for our empirical strategy.

Appendix Table A.10 reports additional robustness checks, showing that our qualitative conclusions are similar when including the six large cities excluded from our main analysis sample because of especially severe measurement error in crime (see Appendix B), estimating negative binomial models, dropping crime outliers, and measuring HHI using birth county to destination city population flows.[31] Results for property crimes are also similar when we estimate linear models where the dependent variable is the log number of crimes.[32]

5.3 Mechanisms

The previous results show that social connectedness reduces city-level crime rates, demonstrate the robustness of this finding, and support the validity of our empirical strategy. So far, we have estimated the overall effect of social connectedness on crime rates. We next present results that clarify our main finding and the underlying mechanisms.

One possible explanation is that social connectedness reduces crime by increasing the probability that criminals are identified and punished. This mechanism predicts that social connectedness should primarily reduce crimes that tend to be witnessed. However, Table 3 shows that social connectedness reduces crimes that are more and less likely to have witnesses: burglary and motor vehicle theft are less likely to have witnesses than robbery or assault, yet the estimates are similar in magnitude for all of these crimes.[33] This suggests that the effect of social connectedness stems in part from other mechanisms, such as effects on norms, values, or skills.

Data limitations prevent us from directly estimating the effects of social connectedness on all potential determinants of crime. However, we can partly assess the importance of observed factors by including them as controls in equation (11). For example, consider the black unemployment rate. If social connectedness increased the probability of employment for young adults and this in turn led to a decrease in crime, then including the black unemployment rate in (11) would attenuate the coefficient on HHI. However, an attenuation of the coefficient does not necessarily imply that employment is a mechanism, as the reduction in crime could cause higher employment, or social connectedness could independently cause lower crime and lower unemployment. An attenuated

[31]We prefer equation (11) over a negative binomial model because it requires fewer assumptions to generate consistent estimates of δ (e.g., Wooldridge, 2002).

[32]From log linear models, the estimate of δ is -0.069 (0.030) for burglary, -0.061 (0.032) for larceny, and -0.135 (0.043) for motor vehicle theft. These are similar to the estimates in Table 3.

[33]Unlike larceny or motor vehicle theft, a robbery features the use of force or threat of force. Consequently, robberies are witnessed by at least one individual (the victim).

coefficient would only suggest the variable in question as a potential mechanism. On the other hand, if the estimated effect of HHI on crime does not change when adding an observed variable, this implies they are not the underlying mechanism.

Table 5 explores several possibilities. We focus on years 1980-1989 because African American-specific covariates from the Census are not available for 1960 or 1990, and the crack index from Fryer et al. (2013) is only available from 1980-forward. Panel A presents results for the 406 cities with non-missing African-American specific covariates, and Panel B contains results for the 78 cities for which the Fryer et al. (2013) crack index is also available.

Column 1 contains the estimate of δ from our baseline specification. In column 2, we add black demographic and economic covariates, including the share of African Americans with a high school and college degree, and the black unemployment rate.[34] Column 3 adds the black homeownership rate, column 4 adds the share of black households headed by a single female, and column 5 adds both of these variables. In column 6 of Panel B, we add the crack index from Fryer et al. (2013), and column 7 adds all variables. Estimates of δ are extremely similar across these specifications. This suggests that the effect of social connectedness on crime is not mediated by short-run effects on employment, education, homeownership, the prevalence of single parents, or crack cocaine use.

Social connectedness also could affect the community's relationship with police. For example, individuals in more connected destinations might be more or less likely to report crimes to police or cooperate with investigations. Data limitations again prevent a full examination of these issues. However, the scope for under- or over-reporting of crimes is negligible for murder, and relatively small for robbery and motor vehicle theft, because these crimes are more likely to be reported to police (Blumstein, 2000; Tibbetts, 2012). Net of any effects on the relationship with police, we find that social connectedness reduces crime.

Mechanisms like the development of norms, values, or skills predict that social connectedness

[34] Additional black demographic and economic covariates include percent age 5-17, 18-64, and 65+, and percent female. Data limitations prevent us from including African American-specific variables for log median family income, labor force participation rate, and manufacturing employment share.

among Southern black migrants should especially reduce crime committed by African American youth. To examine this, we use FBI ASR data, which provide the age, sex, and race of offenders for crimes resulting in arrest starting in 1980. We focus on murders because arrest rates for other well-measured crimes are much lower.[35] As seen in Table 6, social connectedness particularly reduces murders committed by black youth: the elasticity for this group is twice as large as for black adults and non-black individuals. We estimate negative and statistically significant effects for black adults, consistent with either social connectedness having persistent effects on determinants of crime, like norms or skills, or state dependence in criminal activity (Nagin and Paternoster, 1991). Peer effects provide a natural explanation for the reduction in crime among non-black individuals, as described in our model.

Are the effects of social connectedness on crime persistent? Social connectedness could permanently change young individuals' norms, values, and skills, effectively shifting some cities to a low crime equilibrium. Alternatively, the effects could dissipate over time, as migrants from the South age and eventually die. Figure 2, introduced above, displays the estimated effects of social connectedness on crime in five-year intervals from 1960-2009. Both Panels A and B show a decline in the size of effects from 1985-2009. A natural explanation for this is a decline in the correlation between our measure of social connectedness and actual social connectedness. To examine this further, we calculate the share of 14-17 year olds who are living in the North, Midwest, or West regions and were born in the South or live with an adult born in the South. As seen in Figure 3, the share of black children with ties to the South declined from 1980-forward. Taken together, Figures 2 and 3 suggest that the stock of connected adults is key to the effects we estimate.[36]

[35]From 1980-2009, 74 percent of murders were cleared, while only 29 percent of robberies and 15 percent of motor vehicle thefts were cleared.

[36]Another potential explanation is that individuals committing crime in the 2000s, when crime rates were lower, were inframarginal and not affected by social connectedness. To examine this, we estimate whether the effect of social connectedness from 2000-2009 differs across cities with higher and lower predicted crime rates. In particular, we estimate equation (11) using data from 1995-1999 and use the coefficients from this regression to predict crime rates from 2000-2009 based on economic and demographic covariates. We include $\ln(\text{HHI}_k)$ and $\ln(N_k)$ in the 1995-1999 regression, but replace these variables with their mean when constructing predicted crime rates. We also use state-specific linear trends in place of state-by-year fixed effects for the 1995-1999 regressions. There is little evidence of a negative effect of social connectedness from 2000-2009, even for the cities with higher predicted crime rates (Appendix Table A.11), suggesting that this alternative explanation is less relevant.

5.4 Understanding the Role of Peer Effects

Finally, we use the model in Section 3 to examine the role of peer effects in facilitating the relationship between social connectedness and city-level crime rates. This model allows us to decompose the overall effect of social connectedness into the direct effect on African Americans with ties to the South and indirect effects due to peer effects.

The model connects the total effect of HHI on city-level crime, δ, to the effect of HHI on crime for African Americans with ties to the South and peer effects. In particular, equations (7)-(10) imply that the elasticity of the city-level crime rate with respect to Southern black HHI, δ, can be written

$$\delta = \varepsilon^s r^s \left[P^b(P^{s|b}m^s + (1-P^{s|b})m^n) + (1-P^b)m^w\right], \tag{13}$$

where $\delta \equiv (d\bar{C}/d\text{HHI}^s)(\text{HHI}^s/\bar{C})$ is the parameter of interest in our regressions, $\varepsilon^s \equiv (\partial F^s/\partial \text{HHI}^s)$ (HHI^s/F^s) captures the direct effect of HHI on the crime rate of African Americans with ties to the South, $r^s \equiv \bar{C}^s/\bar{C}$ is the ratio of the crime rate among African Americans with ties to the South to the overall crime rate, P^b is the black population share, $P^{s|b}$ is the share of African Americans with ties to the South, and m^s, m^n, and m^w are peer effect multipliers defined in equations (7)-(10).

We use equation (13) to examine which direct effect (ε^s) and peer effect (m^s, m^n, m^w) parametrizations are consistent with our central estimate of δ for murder. We set the black population share $P^b = 0.14$ and the share of the black population with ties to the South $P^{s|b} = 0.67$.[37] We do not observe the crime rate among African Americans with ties to the South. In the FBI data, 51 percent of the murders resulting in arrest are attributed to African Americans. If crime rates are equal among African Americans with and without ties to the South, then $r^s = 3.6$.[38]

[37]The black population share in our sample is 0.14 in 1980. As seen in Figure 3, the share of African American youth living in the North with ties to the South is 0.67 in 1980.

[38]If crime rates are equal among African Americans with and without ties to the South, then $\bar{C}^s = \bar{C}^b$, where $\bar{C}^b \equiv C^b/N^b$ is the crime rate among all African Americans. As a result, $r^s = (C^b/N^b)/(C/N) = (C^b/C)/(N^b/N) = 0.51/0.14$, where C and N are the total number of crimes and individuals. To the extent that African Americans with ties to the South commit less crime than African Americans without ties to the South, we will overstate r^s and understate the direct effect, ε^s.

We make several simplifying assumptions about peer effects. First, we assume that own-group peer effects are equal across all three groups.[39] Second, we assume that cross-group peer effects between non-black individuals and both groups of African Americans are equal. Third, we assume that cross-group peer effects are symmetric in terms of elasticities.[40] The first assumption implies that $J_{11} = J_{22} = J_{33}$, and the second implies that $J_{12} = J_{21}$, $J_{13} = J_{23}$, and $J_{31} = J_{32}$. Letting E_{ab} denote the elasticity form of J_{ab}, these three assumptions imply that $E_{11} = E_{22} = E_{33}$, $E_{12} = E_{21}$, and $E_{13} = E_{23} = E_{31} = E_{32}$.

We draw on previous empirical work to guide our parametrization of peer effects. As detailed in Appendix E, the literature suggests on-diagonal values of J (own-group peer effects) between 0 and 0.5 and off-diagonal values of J (cross-group peer effects) near zero (Case and Katz, 1991; Glaeser, Sacerdote and Scheinkman, 1996; Ludwig and Kling, 2007; Damm and Dustmann, 2014).[41] We consider on-diagonal values of J of 0, 0.25, and 0.5. We allow for sizable peer effects between African Americans with and without ties to the South, and we parametrize the cross-race effects so that elasticities equal 0 or 0.1. Given values of $(r^s, P^b, P^{s|b}, m^s, m^n, m^w)$ and our estimate of δ, equation (13) yields a unique value for ε^s. Equations (7)-(9) then allow us to solve for the effect of a change in Southern black HHI on crime rates for each group.[42]

Table 7 maps the estimated effect of social connectedness on the city-level murder rate to the effect on murder rates of various groups under different peer effect parametrizations.[43] We consider a one standard deviation increase in log HHI, equal to 0.792, which decreases the total murder rate by 13 percent according to the estimate in Table 3. This yields a decrease in the murder rate of

[39] We are aware of no evidence suggesting that own-group peer effects differ for black versus non-black youth.

[40] Given the differences in crime rates between black and non-black individuals, we believe that assuming symmetric cross-group elasticities is more appropriate than assuming symmetric cross-group linear effects (J).

[41] Estimates from previous work are valuable, but are not necessarily comparable to each other or our setting, as they rely on different contexts, identification strategies, data sources, and crime definitions.

[42] In particular, $(d\bar{C}^s/d\text{HHI}^s)(\text{HHI}^s/\bar{C}^s) = \varepsilon^s m^s$, $(d\bar{C}^n/d\text{HHI}^s)(\text{HHI}^s/\bar{C}^n) = \varepsilon^s m^n(\bar{C}^s/\bar{C}^n)$, and $(d\bar{C}^w/d\text{HHI}^s)(\text{HHI}^s/\bar{C}^w) = \varepsilon^s m^w(\bar{C}^s/\bar{C}^w)$. The assumption that crime rates are equal among African Americans with and without ties to the South implies that $\bar{C}^s/\bar{C}^n = 1$. The same assumption, combined with the fact that 51 percent of murders are attributed to African Americans in the UCR data, implies that $\bar{C}^s/\bar{C}^w = [(C^b/C)/(1-C^b/C)][(1-P^b)/P^b] = 6.39$. The direct effect of Southern black HHI on crimes by African Americans with ties to the South is ε^s, the overall effect is $\varepsilon^s m^s$, and the difference is due to peer effects.

[43] Under all peer effect parametrizations in Table 7, the equilibrium is stable, and the assumptions underlying Proposition 1 are true.

African Americans with ties to the South between 37 percent, when there are no cross-group peer effects (column 1), and 19 percent, when peer effects operate across all groups (column 7). The murder rate of African Americans without ties to the South decreases by 0-21 percent, while the murder rate of non-black individuals decreases by 0-7 percent. Depending on the parametrization, up to 82 percent of the effect on African Americans with ties to the South is driven by peer effects. The existing evidence on peer effects suggests placing the most emphasis on columns 3 and 4, which imply that a one standard deviation increase in social connectedness reduces the murder rate of African Americans with ties to the South by 33 and 27 percent and reduces the murder rate of African Americans without ties to the South by 9 and 8 percent. In columns 3 and 4, peer effects account for 30 and 32 percent of the effect on African Americans with ties to the South. Peer effects clearly could play an important role in amplifying the effect of social connectedness on crime.

6 Conclusion

This paper estimates the effect of social connectedness on crime across U.S. cities from 1960-2009. We use a new source of variation in social connectedness stemming from birth town migration networks among millions of African Americans from the South. A one standard deviation increase in social connectedness leads to a precisely estimated 13 percent decrease in murder and a 9 percent decrease in motor vehicle thefts. We find that social connectedness also leads to sizable and statistically significant reductions in robberies, assaults, burglaries, and larcenies. Social connectedness reduces crimes that are more and less likely to have witnesses, which suggests that an increased probability of detection is not the only mechanism through which social connectedness reduces crime. Overall, our results appear to be driven by stronger relationships among older generations reducing crime committed by youth.

Our results highlight the importance of birth town level social ties in reducing violent and property crimes in U.S. cities. Although we have focused on African Americans, social connectedness could have similar effects for other groups. For example, social ties among immigrants could reduce crime and generate other desirable outcomes. While the benefits of these social ties must be weighed against any offsetting effects (e.g., on assimilation), the characteristics of social networks could prove valuable in achieving difficult economic and social milestones in present-day developed economies.

In future work, we plan to use our new source of variation in social connectedness to study its long-run effects on individuals' education, employment, marriage, and fertility. Evidence on these effects is of independent interest and would improve our understanding of the negative effects on crime documented in this paper.

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Table 1: The Relationship between Social Connectedness and 1911-1916 Murder Rates

	Dependent variable: Log HHI, Southern black migrants			
	(1)	(2)	(3)	(4)
Log mean murder rate, 1911-1916	0.010	0.073	-0.071	-0.021
	(0.147)	(0.101)	(0.153)	(0.084)
p-value, H_0 : coefficient equals 0	[0.948]	[0.476]	[0.645]	[0.801]
Log number, Southern black migrants		x		x
Inverse probability weighted			x	x
R2	0.00	0.43	0.00	0.55
N (cities)	46	46	46	46

Notes: The sample contains cities in the North, Midwest, and West Census regions with at least 100,000 residents in 1920. We exclude murder rates based on less than five deaths in constructing the mean murder rate from 1911-1916. In columns 3-4, we use inverse probability weights (IPWs) because the sample of cities for which we observe murder rates from 1911-1916 differs on observed characteristics from our main analysis sample. We construct IPWs using fitted values from a logit model, where the dependent variable is an indicator for a city having murder rate data for at least one year from 1911-1916, and the explanatory variables are log population, percent black, percent age 5-17, percent age 18-64, percent age 65+, percent female, percent with a high school degree or more, percent with a college degree or more, log land area, log median family income, unemployment rate, labor force participation rate, and manufacturing employment share, all measured in 1980. Heteroskedastic-robust standard errors in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Sources: Census (1922, p. 64-65) , Duke SSA/Medicare data, Census city data book

Table 2: Five-Year Migration Rates, Southern Black Migrants Living Outside of the South

	1955-1960 (1)	1965-1970 (2)	1975-1980 (3)	1985-1990 (4)	1995-2000 (5)
Percent living in same state	93.1	95.5	96.2	96.0	95.9
Same county	86.4	90.4	93.8	77.2	93.8
Same house	33.0	54.0	72.8	77.2	79.1
Different house	53.4	36.4	21.0	-	14.7
Different county	-	4.3	2.4	-	2.1
Unknown	6.7	0.8	-	18.8	-
Percent living in different state	6.9	4.5	3.8	4.0	4.1
Not in South	4.0	2.8	1.4	1.2	1.0
In South	2.9	1.6	2.4	2.9	3.1

Notes: Sample restricted to African Americans who were born in the South from 1916-1936 and were living in the North, Midwest, or West regions five years prior to the census year. The 1990 data do not contain detailed information on within-state moves. The 2000 data contain information on public use microdata areas (PUMAs), which are defined by the Census Bureau and contain at least 100,000 residents, instead of counties.
Sources: Census IPUMS, 1960-2000

Table 3: The Effect of Social Connectedness on Crime, 1960-2009

	Dependent variable: Number of offenses reported to police						
	Murder (1)	Rape (2)	Robbery (3)	Assault (4)	Burglary (5)	Larceny (6)	Motor Vehicle Theft (7)
Log HHI, Southern black migrants	-0.161***	-0.046	-0.186***	-0.136***	-0.098***	-0.064*	-0.114**
	(0.040)	(0.036)	(0.034)	(0.044)	(0.030)	(0.036)	(0.045)
Log number, Southern black migrants	x	x	x	x	x	x	x
Demographic covariates	x	x	x	x	x	x	x
Economic covariates	x	x	x	x	x	x	x
State-year fixed effects	x	x	x	x	x	x	x
Pseudo R2	0.812	0.869	0.945	0.926	0.945	0.939	0.930
N (city-years)	19,254	18,058	19,254	19,254	19,254	19,254	19,254
Cities	479	479	479	479	479	479	479

Notes: Table displays estimates of equation (11). Demographic covariates include log population, percent black, percent age 5-17, percent age 18-54, percent 65+, percent female, percent with high school degree, percent with college degree, and log land area. Economic covariates include log median family income, unemployment rate, labor force participation rate, and manufacturing employment share. Standard errors, clustered at the city level, are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Sources: FBI UCR, Duke SSA/Medicare data, Census city data book

Table 4: The Effect of Social Connectedness on Murder, 1960-2009, Robustness

	Dependent variable: Number of murders reported to police							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log HHI, Southern black migrants	-0.158***	-0.146***	-0.163***	-0.167***	-0.151***	-0.130***	-0.146***	-0.164***
	(0.039)	(0.045)	(0.040)	(0.046)	(0.040)	(0.038)	(0.040)	(0.044)
Log number, Southern black migrants	x	x	x		x	x	x	x
State-year fixed effects	x	x	x	x	x	x	x	x
Demographic covariates	x		x	x	x	x	x	x
Economic covariates	x	x		x	x	x	x	x
Indicators for number of Southern black migrants				x				
Log HHI, Southern white migrants					x			
Log number, Southern white migrants					x			
Log HHI, immigrants					x			
Log number, immigrants					x			
Racial fragmentation and percent Hispanic						x		
Birth county covariates							x	
Share of Southern black migrants influenced by birth town migration network								x
Pseudo R2	0.816	0.807	0.814	0.817	0.817	0.817	0.817	0.816
N (city-years)	15,454	15,454	15,454	15,454	15,454	15,454	15,454	15,454
Cities	470	470	470	470	470	470	470	470

Notes: Table displays estimates of equation (11). Demographic and economic covariates are defined in the note to Table 3. Indicators for the number of Southern black migrants correspond to deciles. Racial fragmentation is one minus an HHI of racial population shares. Birth county covariates include migrant-weighted averages of black farm ownership rate, black literacy rate, black population density, percent black, and percent rural, all measured in the 1920 Census, plus Rosenwald school exposure. Column 8 includes an estimate of the share of migrants that chose their destination because of their birth town migration network. We estimate this variable using a structural model of location decisions, as described in Appendix D. We include log population in every specification. Standard errors, clustered at the city level, are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Sources: FBI UCR, Duke SSA/Medicare data, Census city data book, 1920 Census, Aaronson and Mazumder (2011)

Table 5: The Effect of Social Connectedness on Murder, 1980-1989, Possible Mechanisms

	Dependent variable: Number of murders reported to police						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All cities with African American-specific covariates							
Log HHI, Southern black migrants	-0.192***	-0.215***	-0.196***	-0.208***	-0.220***		
	(0.044)	(0.042)	(0.043)	(0.043)	(0.039)		
Log number, Southern black migrants	x	x	x	x	x		
State-year fixed effects	x	x	x	x	x		
Demographic covariates	x	x	x	x	x		
Economic covariates	x	x	x	x	x		
Black demographic and economic covariates		x			x		
Black homeownership rate			x		x		
Share of black households headed by single woman				x	x		
Pseudo R2	0.816	0.819	0.816	0.817	0.820		
N (city-years)	4,022	4,022	4,022	4,022	4,022		
Cities	406	406	406	406	406		
Panel B: All cities with African American-specific covariates and crack index							
Log HHI, Southern black migrants	-0.223***	-0.243***	-0.218***	-0.226***	-0.220***	-0.221***	-0.218***
	(0.052)	(0.048)	(0.053)	(0.048)	(0.043)	(0.053)	(0.044)
Log number, Southern black migrants	x	x	x	x	x	x	x
State-year fixed effects	x	x	x	x	x	x	x
Demographic covariates	x	x	x	x	x	x	x
Economic covariates	x	x	x	x	x	x	x
Black demographic and economic covariates		x			x		x
Black homeownership rate			x		x		x
Share of black households headed by single woman				x	x		x
Crack index						x	x
Pseudo R2	0.838	0.841	0.838	0.840	0.842	0.838	0.842
N (city-years)	776	776	776	776	776	776	776
Cities	78	78	78	78	78	78	78

Notes: Table displays estimates of equation (11). Demographic and economic covariates are defined in the note to Table 3. Black demographic and economic covariates include percent age 5-17, 18-64, and 65+, percent female, percent of population at least 25 years old with a high school degree, percent of population at least 25 years old with a college degree, and unemployment rate. Crack index is from Fryer et al. (2013). Standard errors, clustered at the city level, are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Sources: FBI UCR, Duke SSA/Medicare data, Census city data book, Fryer et al. (2013)

Table 6: The Effect of Social Connectedness on Murder, 1980-2009, by Age-Race Group

	Dependent variable: Number of murders resulting in arrest for age-race group				
	All	Black Youth	Black Adults	Non-Black Youth	Non-Black Adults
	(1)	(2)	(3)	(4)	(5)
Log HHI, Southern black migrants	-0.154***	-0.391***	-0.218***	-0.187	-0.140**
	(0.051)	(0.093)	(0.062)	(0.124)	(0.066)
Log number, Southern black migrants	x	x	x	x	x
Demographic covariates	x	x	x	x	x
Economic covariates	x	x	x	x	x
State-year fixed effects	x	x	x	x	x
Pseudo R2	0.743	0.631	0.772	0.382	0.581
N (city-years)	10,969	10,969	10,969	10,969	10,969
Cities	468	468	468	468	468

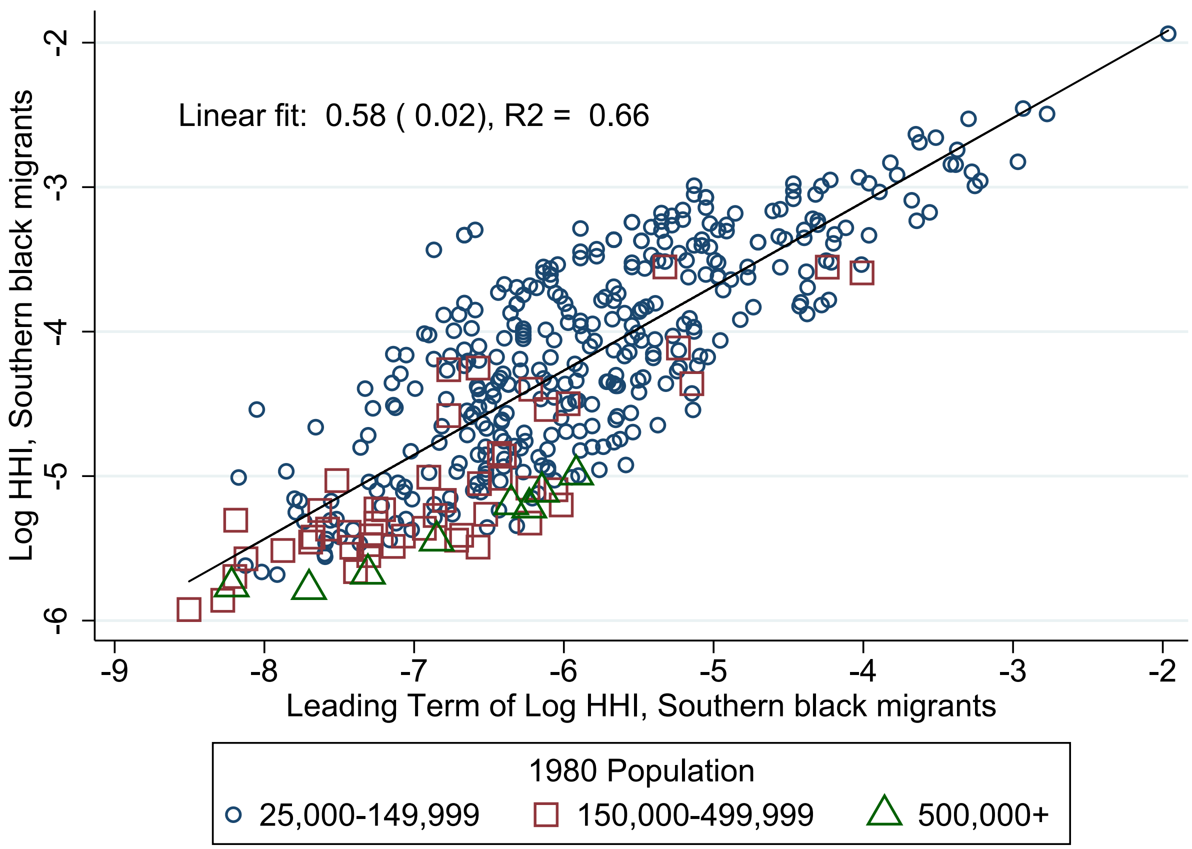
Notes: Table displays estimates of equation (11). Regressions include the same covariates used in Table 3. Standard errors, clustered at the city level, are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Sources: FBI UCR, Duke SSA/Medicare data, Census city data book

Table 7: The Role of Peer Effects in the Effect of Social Connectedness on Crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Peer effect parametrization							
$J_{11} = J_{22} = J_{33}$ (own-group)	0	0.25	0.25	0.25	0.5	0.5	0.5
$J_{12} = J_{21}$ (cross-group, black)	0	0	0.2	0.2	0	0.4	0.4
$J_{13} = J_{23}$ (cross-race, non-black on black)	0	0	0	0.67	0	0	0.67
$J_{31} = J_{32}$ (cross-race, black on non-black)	0	0	0	0.015	0	0	0.015
Implied peer effect elasticities							
$E_{11} = E_{22} = E_{33}$ (own-group)	0	0.25	0.25	0.25	0.5	0.5	0.5
$E_{12} = E_{21}$ (cross-group, black)	0	0	0.2	0.2	0	0.4	0.4
$E_{13} = E_{23}$ (cross-race, non-black on black)	0	0	0	0.1	0	0	0.1
$E_{31} = E_{32}$ (cross-race, black on non-black)	0	0	0	0.1	0	0	0.1
Implied peer effect multipliers							
m^s (blacks with ties to South)	1	1.33	1.44	1.48	2	5.56	8.92
m^n (blacks without ties to South)	0	0	0.38	0.43	0	4.44	7.81
m^w (non-black)	0	0	0	0.04	0	0	0.50
Percent change in murder rate due to one standard deviation increase in log HHI, Southern black migrants							
City-level murder rate	-12.8	-12.8	-12.8	-12.8	-12.8	-12.8	-12.8
Murder rate among non-blacks	0	0	0	-4.7	0	0	-7.2
Murder rate among blacks	-25.0	-25.0	-25.0	-20.7	-25.0	-25.0	-18.4
Among blacks without ties to South	0	0	-8.8	-7.8	0	-21.4	-16.8
Among blacks with ties to South	-37.3	-37.3	-33.0	-27.1	-37.3	-26.8	-19.2
Direct effect of HHI	-37.3	-28.0	-23.0	-18.3	-18.7	-4.8	-2.1
Peer effect	0	-9.3	-10.0	-8.8	-18.7	-22.0	-17.0

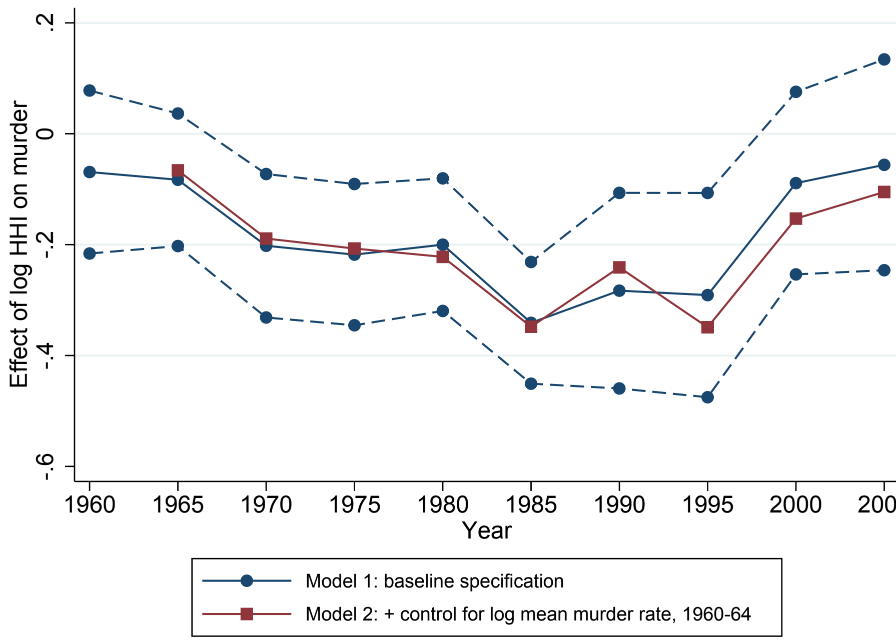
Notes: The top half of Table 7 describes the peer effect parametrizations that we consider. The bottom half decomposes the effect of a one standard deviation increase in social connectedness into changes in murder rates among different groups. See text for details.
Sources: FBI UCR, Duke SSA/Medicare data, Census city data book

Figure 1: The Top Sending Town Accounts for Most of the Variation in Social Connectedness

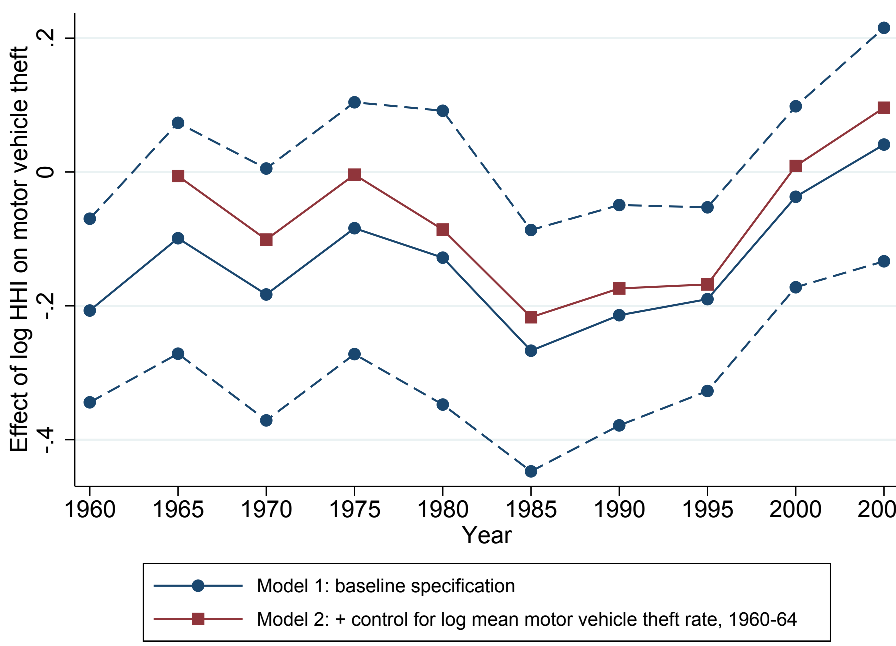


Notes: The leading term of HHI equals the log squared percent of migrants from the top sending town. Figure contains 412 cities.
Source: Duke SSA/Medicare data

Figure 2: The Effect of Social Connectedness on Murder and Motor Vehicle Theft, Robustness to Controlling for 1960-1964 Crime Rate



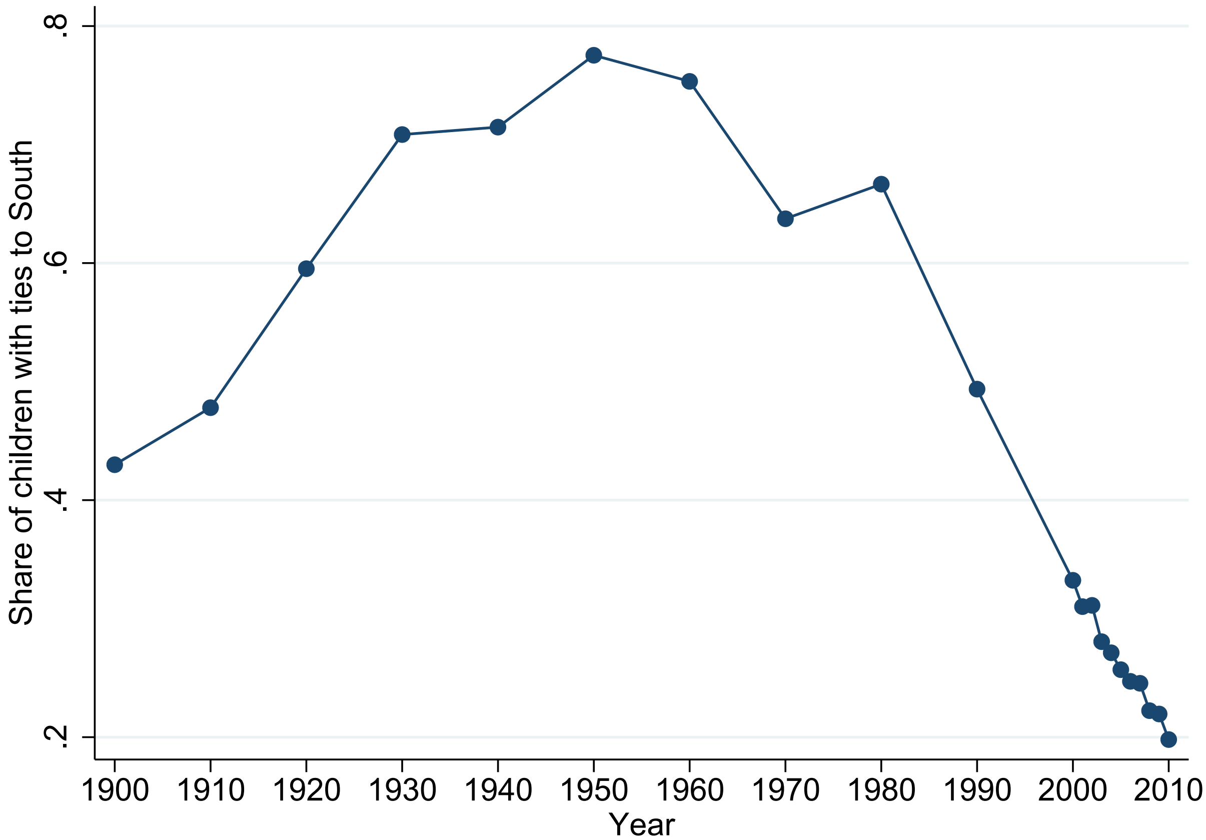
(a) Murder



(b) Motor Vehicle Theft

Notes: Figure shows point estimates and 95-percent confidence intervals from estimating equation (11) separately for year 1960-64, 1965-69, and so on. Model 1 includes the same covariates used in Table 3, and model 2 additionally controls for the log mean crime rate from 1960-64.
Sources: FBI UCR, Duke SSA/Medicare data, Census city data book

Figure 3: The Share of African American Children Living in the North, Midwest, or West with Ties to the South



Notes: Figure plots the share of individuals age 14-17 who are living in the North, Midwest, or West regions who were born in the South or live in the same household as an adult born in the South.
Sources: IPUMS Decennial Census (1900-2000) and American Community Survey (2001-2010)

Appendices - For Online Publication

A Theoretical Details

A.1 Proof of Proposition 1

To prove Proposition 1, we show that the assumptions of a stable equilibrium and non-negative peer effects (i.e., elements of J) imply that the peer effect multipliers m^s, m^n, and m^w are non-negative.

Let $\lambda_1, \lambda_2, \lambda_3$ be the eigenvalues of the 3×3 matrix J. The spectral radius of J is defined as $\rho(J) \equiv \max\{|\lambda_1|, |\lambda_2|, |\lambda_3|\}$. To ensure the equilibrium is stable, we assume that $\rho(J) < 1$. In each peer effect parametrization considered in Table 7, all eigenvalues are real and lie in $[0, 1)$, and this condition is satisfied.

The on-diagonal elements of J (J_{11}, J_{22}, J_{33}) are less than one in a stable equilibrium. This follows from the facts that the spectral radius is less than one if and only if $\lim_{k\to\infty} J^k = 0$ and $\lim_{k\to\infty} J^k = 0$ implies that the on-diagonal elements of J are less than one.

In a stable equilibrium, we also have that $\det(I - J) > 0$, where I is the 3×3 identity matrix. This follows from our assumption that $\rho(J) < 1$, the fact that $\det(J) = \lambda_1\lambda_2\lambda_3$, and the fact that $\det(J) = \lambda_1\lambda_2\lambda_3$ if and only if $\det(I - J) = (1 - \lambda_1)(1 - \lambda_2)(1 - \lambda_3)$.

It is straightforward to show that

$$\begin{aligned} \det(I - J) &= (1 - J_{11})[(1 - J_{22})(1 - J_{33}) - J_{23}J_{32}] \qquad \text{(A.1)} \\ &\quad - J_{12}[J_{23}J_{31} + J_{21}(1 - J_{33})] - J_{13}[J_{21}J_{32} + J_{31}(1 - J_{22})] \\ &= (1 - J_{11})m^s - J_{12}m^n - J_{13}m^w, \qquad \text{(A.2)} \end{aligned}$$

where the second equality uses the peer effect multipliers defined in equations (7)-(9). Because the off-diagonal elements of J are non-negative (by assumption) and the on-diagonal elements of J are less than 1 (as implied by a stable equilibrium), we have that m^n and m^w are non-negative. As a result,

$$0 < \det(I - J) \leq (1 - J_{11})m^s. \qquad \text{(A.3)}$$

Because $J_{11} < 1$, this implies that m^s is non-negative. QED.

B Additional Details on Sample

Our primary measure of crime is annual city-level crime counts from FBI Uniform Crime Report (UCR) data for 1960-2009. UCR data contain voluntary monthly reports on the number offenses reported to police, which we aggregate to the city-year level. These data are used regularly in the literature and represent the best source of city crime rates. However, the UCR data are not perfect. Missing crimes are indistinguishable from true zeros in the UCR. Because cities in our sample almost certainly experience property crime each year, we drop all city-years in which any of the three property crimes (burglary, larceny, and motor vehicle theft) equal zero.

An alternative source of city-level crime counts is the FBI Age-Sex-Race (ASR) data, which report the number of offenses resulting in arrest by age, sex, and race beginning in 1980. The UCR data also report the number of offenses resulting in arrest. In principle, these two data sets, which both rely on reports from police agencies, should lead to similar crime counts. In practice, we found substantial differences between these data sets, especially for large cities.

Appendix Figure A.2 plots the difference between the number of murders in the FBI UCR versus ASR data by annual population. For reference, we draw a vertical line at 500,000 residents and horizontal lines at -100 and 100. We classify each city into one of two groups, based on whether the city has at least five "severe errors," which define to be years in which the absolute value of the difference in the number of crimes is at least 100. While somewhat arbitrary, this classification identifies the most severe instances of disagreement between the UCR and ASR data.

There are six cities with at least five severe errors: Chicago, Detroit, Los Angeles, Milwaukee, New York, and Philadelphia. Appendix Figure A.3 plots the number of murders from the UCR and ASR data over time. There does not appear to be a simple explanation for the differences between the two data sets. As a result, we drop these six cities from our main analysis sample. However, as seen in Panel A of Appendix Table A.10, our results are similar when we include these large cities.[44]

C Additional Details on Variation in Social Connectedness

Appendix Table A.5 examines the correlation between log HHI and several demographic and economic covariates. In particular, we regress log HHI on various covariates for the 236 cities observed in every decade from 1960 to 2000. To facilitate comparisons, we normalize all variables, separately for each decade, to have mean zero and standard deviation one. Only the log number of migrants and the manufacturing employment share are consistently correlated with log HHI. The negative correlation between log HHI and the log number of migrants arises because a large number of migrants necessarily came from many sending towns, due to the small size of Southern towns relative to Northern cities. The positive correlation between log HHI and the manufacturing employment share arises because social interactions in location decisions guided migrants to destinations with higher manufacturing employment, which was especially attractive to African American workers (Stuart and Taylor, 2017). Appendix Table A.6 shows results when adding a number of covariates measured among African-Americans.[45]

Appendix Figure A.4 further describes the cross-city variation in social connectedness by plotting log HHI and the log number of Southern black migrants. Our regressions identify the effect of social connectedness on crime with variation in log HHI conditional on the log number of migrants in a city (and other covariates), which is variation in the vertical dimension of Figure A.4. There is considerable variation in log HHI conditional on the log number of migrants.

[44] Mosher, Miethe and Hart (2011) discuss measurement error in the UCR data in detail, but do not discuss the discrepancies we have identified between the UCR and ASR data.

[45] African American covariates include percent age 5-17, 18-64, and 65+, percent female, percent with a high school degree, percent with a college degree, and the unemployment rate. These variables are not available for 1960. In 1990, only the education variables are available; for the other variables, we linearly interpolate the 1980 and 2000 values.

D Estimating a Model of Social Interactions in Location Decisions

Appendix D describes a structural model of social interactions in location decisions. This model allows us to estimate the share of migrants that chose their destination because of social interactions. We include this variable in our regressions to examine whether the effect of social connectedness is driven by variation across cities in unobserved characteristics of migrants.

D.1 Model of Social Interactions in Location Decisions

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 town 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 social interactions, the destination in H_i is most preferred, and destinations in M_i are preferred over those in L_i.[46] A migrant never moves to a destination in L_i. A migrant chooses a destination in M_i if and only if his neighbor, $i-1$, chooses the same destination. A migrant chooses a destination in H_i if his neighbor chooses the same destination or his neighbor selects a destination in L_i.[47]

Migrants from the same birth town can 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 $m_{j,k} \equiv \mathbb{P}[k \in M_i | i \in j]$.

Migrants with many destinations in their medium preference group will tend to be influenced by the decisions of other migrants. For estimating the effect of social connectedness on crime, distinguishing between types of migrants is important because migrants that are more influenced by social interactions might differ along several dimensions. For example, migrants with many destinations in their medium preference group might be negatively selected in terms of earnings ability or be more pro-social, and these characteristics might bias estimates of δ is equation (11).

The probability that migrant i moves to destination k given that his neighbor moves there is

$$\begin{aligned}\rho_{j,k} \equiv \mathbb{P}[D_{i,j,k} = 1 | D_{i-1,j,k} = 1, i \in j] &= \mathbb{P}[k \in H_i | i \in j] + \mathbb{P}[k \in M_i | i \in j] \qquad (A.4)\\ &= h_{j,k} + m_{j,k}, \qquad (A.5)\end{aligned}$$

where $D_{i,j,k}$ equals one if migrant i moves from j to k and zero otherwise.

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 $m_{j,k} = \nu_{j,k}(1 - h_{j,k})$. We use $\nu_{j,k}$ to derive a simple sequential estimation approach.

[46] The assumption that H_i is a non-empty singleton ensures that migrant i has a well-defined location decision in the absence of social interactions. 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.

[47] This model shares a similar structure as Glaeser, Sacerdote and Scheinkman (1996) in that some agents imitate their neighbors. However, we differ from Glaeser, Sacerdote and Scheinkman (1996) in that we model the interdependence between various destinations (i.e., this is a multinomial choice problem) and allow for more than two types of agents.

In equilibrium, the probability that a randomly chosen migrant i moves from j to k is

$$\begin{aligned} P_{j,k} \equiv \mathbb{P}[D_{i,j,k} = 1] &= \mathbb{P}[D_{i-1,j,k} = 1, k \in H_i] + \mathbb{P}[D_{i-1,j,k} = 1, k \in M_i] \\ &\quad + \sum_{k' \neq k} \mathbb{P}[D_{i-1,j,k'} = 1, k \in H_i, k' \in L_i] && \text{(A.6)} \\ &= P_{j,k}h_{j,k} + P_{j,k}\nu_{j,k}(1 - h_{j,k}) + \sum_{k' \neq k} P_{j,k'}h_{j,k}(1 - \nu_{j,k'}) && \text{(A.7)} \\ &= P_{j,k}\nu_{j,k} + \left(\sum_{k'=1}^{K} P_{j,k'}(1 - \nu_{j,k'}) \right) h_{j,k}. && \text{(A.8)} \end{aligned}$$

The first term on the right hand side of equation (A.6) is the probability that a migrant's neighbor moves to k, and k is in the migrant's high preference group; in this case, social interaction reinforces the migrant's desire to move to k. The second term is the probability that a migrant follows his neighbor to k because of social interactions. The third term is the probability that a migrant resists the pull of social interactions because town k is in the migrant's high preference group and the neighbor's chosen destination is in the migrant's low preference group.

The share of migrants from birth town j living in destination k that chose their destination because of social interactions equals $m_{j,k}$. As a result, the share of migrants in destination k that chose this destination because of social interactions is

$$m_k \equiv \sum_j N_{j,k} m_{j,k}, \tag{A.9}$$

where $N_{j,k}$ is the number of migrants that moved from j to k. Our goal is to estimate m_k for each destination.

D.2 Estimation

To facilitate estimation, we connect this model to the social interactions (SI) index introduced by Stuart and Taylor (2017). The SI index, $\Delta_{j,k}$, is the expected increase in the number of people from birth town j that move to destination k when an arbitrarily chosen person i is observed to make the same move,

$$\Delta_{j,k} \equiv \mathbb{E}[N_{-i,j,k} | D_{i,j,k} = 1] - \mathbb{E}[N_{-i,j,k} | D_{i,j,k} = 0], \tag{A.10}$$

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 positive social interactions in moving from j to k, while $\Delta_{j,k} = 0$ indicates the absence of social interactions. Stuart and Taylor (2017) show that the SI index can be expressed as

$$\Delta_{j,k} = \frac{C_{j,k}(N_j - 1)}{P_{j,k}(1 - P_{j,k})}, \tag{A.11}$$

where $C_{j,k}$ is the average covariance of location decisions between migrants from town j, $C_{j,k} \equiv \sum_{i \neq i' \in j} \mathbb{C}[D_{i,j,k}, D_{i',j,k}]/(N_j(N_j - 1))$.

The model implies that $C_{j,k}$ equals[48]

$$C_{j,k} = \frac{2P_{j,k}(1-P_{j,k})\sum_{s=1}^{N_j-1}(N_j - s)\left(\frac{\rho_{j,k}-P_{j,k}}{1-P_{j,k}}\right)^s}{N_j(N_j-1)}. \tag{A.12}$$

Substituting equation (A.12) into equation (A.11) and simplifying yields[49]

$$\Delta_{j,k} = \frac{2(\rho_{j,k} - P_{j,k})}{1-\rho_{j,k}}, \tag{A.13}$$

which can be rearranged to show that

$$\rho_{j,k} = \frac{2P_{j,k} + \Delta_{j,k}}{2 + \Delta_{j,k}}. \tag{A.14}$$

We follow the approach described in Stuart and Taylor (2017) to estimate $P_{j,k}$ and $\Delta_{j,k}$ using information on migrants' location decisions from the Duke SSA/Medicare data.[50] We then use equation (A.14) to estimate $\rho_{j,k}$ with our estimates of $P_{j,k}$ and $\Delta_{j,k}$.

Equations (A.5) and (A.8), plus the fact that $m_{j,k} = \nu_{j,k}(1 - h_{j,k})$, imply that

$$\rho_{j,k} = \nu_{j,k} + \frac{P_{j,k}(1-\nu_{j,k})^2}{\sum_{k'=1}^{K} P_{j,k'}(1-\nu_{j,k'})}. \tag{A.15}$$

We use equation (A.15) to estimate $\nu_j \equiv (\nu_{j,1}, \ldots, \nu_{j,K})$ using our estimates of $(P_{j,1}, \ldots, P_{j,K}, \rho_{j,1}, \ldots, \rho_{j,K})$. We employ a computationally efficient algorithm that leverages the fact that equation (A.15) is a quadratic equation in $\nu_{j,k}$, conditional on $\sum_{k'=1}^{K} P_{j,k'}(1-\nu_{j,k'})$. We initially assume that $\sum_{k'=1}^{K} P_{j,k'}(1-\nu_{j,k'}) = \sum_{k'=1}^{K} P_{j,k'} = 1$, then solve for $\nu_{j,k}$ using the quadratic formula, then construct an updated estimate of $\sum_{k'=1}^{K} P_{j,k'}(1-\nu_{j,k'})$, and then solve again for $\nu_{j,k}$ using the quadratic formula. We require that each estimate of $\nu_{j,k}$ lies in $[0, 1]$. This iterated algorithm converges very rapidly in the vast majority of cases.[51]

We use equation (A.8) to estimate $h_{j,k}$ with our estimates of $\rho_{j,k}$ and $\nu_{j,k}$. Finally, we estimate $m_{j,k}$ using the fact that $m_{j,k} = \rho_{j,k} - h_{j,k}$. We use equation (A.9) to estimate our parameter of interest, m_k, using estimates of $m_{j,k}$ and observed migration flows, $N_{j,k}$.

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

[49] Equation (A.13) results from taking the limit as $N_j \to \infty$, and so relies on N_j being sufficiently large.

[50] We use cross validation to define birth town groups. See Stuart and Taylor (2017) for details.

[51] For 10 birth towns, the algorithm does not converge because our estimates of $P_{j,k}$ and $\rho_{j,k}$ do not yield a real solution to the quadratic formula. We examined the sensitivity of our results to these cases by (1) dropping birth towns for which the algorithm did not converge, (2) estimating $\nu_{j,k}$ and $\sum_{k'=1}^{K} P_{j,k'}(1-\nu_{j,k'})$ as the average of the values in the final four iterations, and (3) forcing $\hat{\nu}_{j,k}$ to equal zero for any (j,k) observation for which the quadratic formula solution does not exist. The motivation for (3) is that our estimates of $P_{j,k}$ and $\rho_{j,k}$ in these 10 cases were consistent with negative values of $\nu_{j,k}$, even though this is not a feasible solution. All three options yielded nearly identical estimates of our variable of interest, m_k. This is not surprising because these 10 birth towns account for a negligible share of the over 5,000 birth towns used to estimate m_k.

D.3 Results

Appendix Figure A.5 displays a histogram of our estimates of the share of migrants that chose their destination because of social interactions, m_k, for cities in the North, Midwest, and West regions. The estimates range from 0 to 0.62. The unweighted average of m_k across cities is 0.26, and the 1980 population weighted average is 0.39.

Appendix Table A.9 examines the relationship between log HHI, the log number of migrants, and m_k. The raw correlation between log HHI and m_k is negative, but when we control for the log number of migrants, log HHI and m_k are positively correlated, as expected. This relationship is similar when including state fixed effects.

Appendix Figure A.6 further describes the relationship between log HHI and m_k. Panel A plots the unconditional relationship between log HHI and m_k, while Panel B plots the relationship conditional on the log number of migrants.[52] When we control for m_k in equation (11), we identify the effect of social connectedness on crime using variation in the vertical dimension of Panel B.

Conditional on the number of migrants in a destination and the share of migrants that chose their destination because of social interactions, variation in social connectedness continues to arise from concentrated birth town to destination city population flows. To see this, consider two hypothetical cities that each have 20 migrants, one-fourth of whom chose their destination because of social interactions. In the low HHI city, the 20 migrants come from five birth towns. Each town sends four migrants, one of whom moves there because of social interactions. As a result, $\text{HHI}_{\text{Low}} = 0.2$. In the high HHI city, the 20 migrants also come from five birth towns. One town sends 12 migrants, three of whom move there because of social interactions. Two towns each send two migrants, one of whom moves there because of social interactions, and two towns each send two migrants, neither of whom is influenced by social interactions. As a result, $\text{HHI}_{\text{High}} = 0.4$.[53] This example is consistent with Figure 1 in that variation in social connectedness arises from the top sending town.

The structural model features local social interactions: each migrant directly influences no more than one migrant.[54] As a result, the model does not distinguish between the case where 12 migrants come from one town, with three migrants influenced by social interactions, and the case where 12 migrants come from three towns, with three migrants influenced by social interactions. Although this model does not capture all possible forms of social interactions, we believe that it likely captures the most relevant threats to the empirical strategy for this paper.

E Details on Peer Effect Parametrization

Appendix E provides additional details on the literature that guides our parametrization of peer effects in Section 5.4.

Case and Katz (1991) find that a one percent increase in the neighborhood crime rate leads to a 0.1 percent increase in a Boston youth's self-reported propensity of committing a crime during the last year (Table 10). This implies that a one percentage point increase in the neighborhood crime

[52]In particular, Panel B plots the residuals from regressing log HHI and m_k on the log number of migrants.

[53]Alternatively, suppose that in the high HHI city, the 20 migrants come from three birth towns. One town sends 12 migrants, three of whom move there because of social interactions, and two towns each send four migrants, one of whom moves there because of social interactions. As a result, $\text{HHI}_{\text{High}} = 0.44$.

[54]However, a single migrant can indirectly influence several migrants.

rate leads to a 0.1 percentage point increase in youth's crime rate, suggesting on-diagonal elements of J close to 0.1.

Glaeser, Sacerdote and Scheinkman (1996) estimate a local social interactions model in which there are two types of agents. Fixed agents are not affected by their peers, and compliers imitate their neighbor. The probability that an agent is a complier thus maps to the on-diagonal elements of J. In Table IIA, the authors report estimates of $f(\pi) = (2-\pi)/\pi$, where π is the probability that an agent is a fixed type. The probability that an agent is a complier is $1-\pi = 1-2/(1+f(\pi))$. Using FBI UCR data on murders across cities for 1970 and 1985, Glaeser, Sacerdote and Scheinkman (1996) report estimates of $f(\pi)$ between 2 and 4.5, implying on-diagonal elements of J between 1/3 and 2/3. For robbery and motor vehicle theft, the authors estimate $f(\pi)$ in the range of 37-155 and 141-382, suggesting diagonal elements of J very close to 1.

Ludwig and Kling (2007) find no evidence that neighborhood violent crime rates affect violent crime arrests among MTO participants age 15-25 (Table 4). These estimates suggest on-diagonal elements of J close to zero.

Damm and Dustmann (2014) estimate the effect of municipality crime rates on refugees' criminal convictions in Denmark. For males, they find that a one percentage point increase in the municipality crime rate leads to a 7-13 percent increase in the probability of conviction over a seven year period from ages 15-21 (Table 3, also see p. 1820). Given an average conviction rate of 46 percent, this translates into a 3-6 percentage point increase in the probability of conviction; we take the midpoint of 4.5. For females, the municipality crime rate has no effect on convictions. Consequently, these estimates imply that a one percentage point increase in the municipality crime rate leads to a $(0.5 \cdot 4.5)/7 \approx 0.32$ percentage point increase in refugees' annual conviction rate. This suggests on-diagonal elements of J close to 1/3. Damm and Dustmann (2014) find that, beyond the impact of the municipality crime rate, the crime rate of co-nationals has an additional impact while the crime rate of immigrants from other countries does not (Table 7). This suggests that cross-group peer effects might be small.

In sum, estimates from Case and Katz (1991) suggest on-diagonal values of J close to 0.1, estimates from Glaeser, Sacerdote and Scheinkman (1996) suggest on-diagonal elements of J close to 0.5 for murder, estimates from Ludwig and Kling (2007) suggest on-diagonal elements of J close to zero, and estimates from Damm and Dustmann (2014) suggest on-diagonal values of J close to 0.3 and off-diagonal elements near zero.

Table A.1: Summary Statistics: Crime and Social Connectedness, 1960-2009

	Mean	SD	First Quartile	Third Quartile	Fraction Zero
Offenses reported to police per 100,000 residents					
Murder	6.8	8.9	1.8	8.9	0.181
Rape	30	28	10	40	0.069
Robbery	219	255	69	277	0.003
Assault	1,137	1,099	287	1,629	0.005
Burglary	1,241	844	675	1,642	0.000
Larceny	3,234	1,776	2,032	4,204	0.000
Motor Vehicle Theft	594	526	264	757	0.000
Population	105,807	132,412	39,796	108,034	-
HHI, Southern Black Migrants	0.019	0.016	0.007	0.028	-
Log HHI, Southern Black Migrants	-4.244	0.792	-4.923	-3.591	-
Top Sending Town Share, Southern Black Migrants	0.061	0.041	0.036	0.073	-
Number, Southern Black Migrants	742	1,679	60	650	-

Notes: Each observation is a city-year. HHI and migrant counts are calculated among all individuals born in the former Confederacy states from 1916-1936. Data on rape is only available starting in 1964. Sample is restricted to cities with less than 500,000 residents in 1980.
Sources: FBI UCR, Duke SSA/Medicare dataset

Table A.2: Summary Statistics: Cities' Average Crime Rates

	Mean	SD	Percentile				
			5	25	50	75	95
Murder	6.8	6.8	1.3	2.7	4.6	8.3	19.6
Rape	29.5	18.6	6.5	16.2	26.5	37.6	66.6
Robbery	217.1	186.5	42.2	93.7	157.3	273.0	632.9
Assault	1,124.8	623.3	326.7	652.8	1,019.4	1,471.9	2,320.4
Burglary	1,239.6	473.3	544.0	895.2	1,189.0	1,534.1	2,095.9
Larceny	3,227.1	1,205.0	1,525.6	2,383.6	3,186.4	3,927.1	5,030.8
Motor Vehicle Theft	588.7	381.9	178.7	314.5	464.5	761.9	1,328.9

Notes: For each city, we construct an average crime rate across years 1960-2009. Table A.2 reports summary statistics of these average crime rates. Sample is restricted to cities with less than 500,000 residents in 1980. Sources: FBI UCR

Table A.3: Summary Statistics: Cities With and Without 1911-1916 Murder Rates

	1911-1916 Murder Rates Observed	
	Yes	No
	(1)	(2)
HHI, Southern black migrants	0.007	0.021
	(0.006)	(0.016)
Number, Southern black migrants	7,999	540
	(16,068)	(2,079)
Population, 1980	549,344	80,839
	(1,099,422)	(170,680)
Percent black, 1980	0.237	0.103
	(0.152)	(0.148)
Percent age 5-17, 1980	0.187	0.196
	(0.0291)	(0.0324)
Percent age 18-64, 1980	0.605	0.621
	(0.0280)	(0.0422)
Percent age 65+, 1980	0.136	0.112
	(0.0223)	(0.0383)
Percent female, 1980	0.530	0.519
	(0.008)	(0.019)
Percent 25+ with HS, 1980	0.489	0.560
	(0.080)	(0.098)
Percent 25+ with College, 1980	0.118	0.137
	(0.048)	(0.078)
Log area, square miles, 1980	3.886	2.729
	(0.986)	(0.888)
Log median family income, 1979	10.85	11.06
	(0.148)	(0.205)
Unemployment rate, 1980	0.0886	0.0708
	(0.033)	(0.030)
Labor force participation rate, 1980	0.458	0.483
	(0.041)	(0.052)
Manufacturing emp. share, 1980	0.213	0.233
	(0.072)	(0.094)
N (cities)	46	369

Notes: Table reports means and, in parentheses, standard deviations. Column 1 contains cities in the North, Midwest, and West regions that are in our main analysis sample and for which we observe murder rates for at least one year from 1911-1916. These cities have at least 100,000 residents in 1920 and at least 5 deaths each year. Column 2 contains cities in the North, Midwest, and West regions that are in our main analysis sample but for which we do not observe homicide rates from 1911-1916.
Sources: Census (1922, p. 64-65) , Duke SSA/Medicare data, Census city data book

Table A.4: The Relationship between Social Connectedness and Measures of Social Capital

	Dependent variable: Log HHI, Southern black migrants							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Cities								
Associational density	0.0708	0.103**					0.110	0.135**
	(0.0574)	(0.0479)					(0.0922)	(0.0589)
Social capital index			0.0432	0.0418			-0.0480	-0.0513
			(0.0568)	(0.0459)			(0.0941)	(0.0554)
Social capital composite index					0.0342	0.0308		
					(0.0557)	(0.0428)		
Log number, Southern black migrants		-0.867***		-0.866***		-0.866***		-0.867***
		(0.0289)		(0.0287)		(0.0287)		(0.0293)
State fixed effects		x		x		x		x
R2	0.007	0.741	0.002	0.739	0.001	0.740	0.008	0.742
N (cities)	484	484	484	484	484	484	484	484
Counties	225	225	225	225	225	225	225	225
Panel B: Cities with Above Median Black Population Share in 1990								
Associational density	0.313***	0.145*					0.509***	0.179*
	(0.0644)	(0.0742)					(0.103)	(0.0964)
Social capital index			0.197***	0.103			-0.257***	-0.0556
			(0.0587)	(0.0725)			(0.0968)	(0.0839)
Social capital composite index					0.176***	0.0847		
					(0.0571)	(0.0678)		
Log number, Southern black migrants		-0.674***		-0.695***		-0.696***		-0.669***
		(0.0502)		(0.0485)		(0.0486)		(0.0507)
State fixed effects		x		x		x		x
R2	0.129	0.598	0.043	0.591	0.034	0.590	0.155	0.603
N (cities)	226	226	226	226	226	226	226	226
Counties	151	151	151	151	151	151	151	151

Notes: All variables are normalized to have mean zero and standard deviation one in the sample used in Panel A. See Rupasingha and Goetz (2008) for definitions of associational density and social capital indices, which are measured at the county level using data from 1988 and 1990. The correlation between the social capital index and the social capital composite index is 0.998. Panel B has less than half the observations as Panel A because percent black in 1990 is missing for some cities. Standard errors, clustered at the county level, are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Sources: Duke SSA/Medicare data, Rupasingha and Goetz (2008)

Table A.5: The Relationship between Social Connectedness and City Covariates, 1960-2000

	Dependent variable: Log HHI, Southern black migrants					
Year covariates are measured:	-	1960	1970	1980	1990	2000
	(1)	(2)	(3)	(4)	(5)	(6)
Log number Southern black migrants	-0.842***	-0.882***	-0.866***	-0.836***	-0.738***	-0.750***
	(0.039)	(0.067)	(0.073)	(0.081)	(0.084)	(0.073)
Log population		0.059	0.019	0.011	-0.060	0.032
		(0.067)	(0.072)	(0.083)	(0.093)	(0.090)
Percent black		0.029	0.001	0.009	-0.058	-0.058
		(0.053)	(0.059)	(0.073)	(0.066)	(0.057)
Percent female		0.003	-0.056	-0.040	-0.023	0.001
		(0.047)	(0.057)	(0.076)	(0.076)	(0.055)
Percent age 5-17		-0.083	0.137	0.228	0.538**	0.336
		(0.145)	(0.195)	(0.238)	(0.246)	(0.285)
Percent age 18-64		-0.067	0.093	0.225	0.585**	0.519*
		(0.119)	(0.200)	(0.244)	(0.258)	(0.314)
Percent age 65+		0.005	0.157	0.320	0.535***	0.420**
		(0.090)	(0.139)	(0.196)	(0.188)	(0.194)
Percent with HS degree		-0.064	-0.086	-0.194**	-0.067	-0.072
		(0.111)	(0.114)	(0.095)	(0.075)	(0.077)
Percent with college degree		0.133*	0.094	0.073	0.121*	0.052
		(0.070)	(0.062)	(0.050)	(0.063)	(0.062)
Log area, square miles		-0.036	0.024	0.018	0.041	-0.029
		(0.050)	(0.061)	(0.069)	(0.077)	(0.081)
Log median family income		-0.010	-0.015	-0.008	-0.222**	-0.059
		(0.080)	(0.080)	(0.088)	(0.088)	(0.063)
Unemployment rate		0.116**	0.153*	0.021	0.018	0.057
		(0.058)	(0.077)	(0.067)	(0.078)	(0.058)
Labor force participation rate		0.032	0.103**	0.036	0.117	-0.044
		(0.028)	(0.051)	(0.089)	(0.097)	(0.049)
Manufacturing employment share		0.206***	0.147**	0.131**	0.149***	0.177***
		(0.056)	(0.059)	(0.054)	(0.046)	(0.044)
State fixed effects	x	x	x	x	x	x
Adjusted	0.744	0.772	0.767	0.761	0.766	0.773
N (cities)	236	236	236	236	236	236

Notes: Sample contains cities that appear in each decade from 1960-2000 for which all covariates in this table are non-missing. We normalize all variables, separately for each regression, to have mean zero and standard deviation one. Heteroskedastic-robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Sources: Duke SSA/Medicare data, Census city data book

Table A.6: The Relationship between Social Connectedness and City Covariates, 1960-2000, Including African American Specific Covariates

	Dependent variable: Log HHI, Southern black migrants			
Year covariates are measured:	1970	1980	1990	2000
	(1)	(2)	(3)	(4)
Log number Southern black migrants	-0.837***	-0.799***	-0.750***	-0.781***
	(0.070)	(0.078)	(0.090)	(0.098)
Log population	0.025	0.038	-0.008	0.061
	(0.079)	(0.085)	(0.096)	(0.097)
Percent black	-0.006	0.011	-0.036	-0.063
	(0.058)	(0.074)	(0.071)	(0.065)
Percent female	-0.087	-0.006	-0.013	0.036
	(0.059)	(0.078)	(0.089)	(0.075)
Percent age 5-17	-0.031	0.217	0.447*	0.499
	(0.215)	(0.256)	(0.264)	(0.322)
Percent age 18-64	-0.086	0.257	0.509*	0.645*
	(0.224)	(0.268)	(0.276)	(0.355)
Percent age 65+	0.054	0.300	0.449**	0.491**
	(0.155)	(0.212)	(0.205)	(0.215)
Percent with HS degree	0.039	-0.133	-0.009	-0.029
	(0.129)	(0.104)	(0.090)	(0.100)
Percent with college degree	0.025	0.007	-0.011	-0.023
	(0.071)	(0.053)	(0.081)	(0.084)
Log area, square miles	0.018	-0.036	-0.008	-0.035
	(0.063)	(0.074)	(0.081)	(0.086)
Log median family income	-0.059	-0.019	-0.185*	-0.054
	(0.091)	(0.086)	(0.097)	(0.080)
Unemployment rate	0.182**	-0.027	-0.059	0.025
	(0.081)	(0.084)	(0.090)	(0.055)
Labor force participation rate	0.092*	0.020	0.091	-0.037
	(0.051)	(0.087)	(0.103)	(0.054)
Manufacturing employment share	0.182***	0.155***	0.153***	0.181***
	(0.063)	(0.057)	(0.051)	(0.046)
African American-Specific Covariates:				
Percent female	0.032	-0.088	-0.003	0.075
	(0.044)	(0.060)	(0.073)	(0.071)
Percent age 5-17	0.122	0.099	0.144	-0.139
	(0.076)	(0.112)	(0.150)	(0.171)
Percent age 18-64	0.134	0.042	0.194	-0.058
	(0.085)	(0.128)	(0.177)	(0.207)
Percent age 65+	0.046	0.053	0.100	-0.015
	(0.054)	(0.068)	(0.087)	(0.103)
Percent with HS degree	-0.188**	-0.075	-0.113	-0.036
	(0.074)	(0.072)	(0.075)	(0.071)
Percent with college degree	0.146***	0.119*	0.124	0.062
	(0.052)	(0.064)	(0.078)	(0.077)
Unemployment rate	-0.080*	0.053	0.111*	0.105***
	(0.046)	(0.072)	(0.059)	(0.040)
State fixed effects	x	x	x	x
Adjusted R2	0.775	0.762	0.767	0.777
N (cities)	236	236	236	236

Notes: African American-specific covariates are not available for 1960. See note to Table A.5.
Sources: Duke SSA/Medicare data, Census city data book

Table A.7: The Effect of Social Connectedness on Crime, 1960-2009, Results for All Explanatory Variables

	Dependent variable: Number of offenses reported to police						
	Murder (1)	Rape (2)	Robbery (3)	Assault (4)	Burglary (5)	Larceny (6)	Motor Vehicle Theft (7)
Log HHI, Southern black migrants	-0.161***	-0.046	-0.186***	-0.136***	-0.098***	-0.064*	-0.114**
	(0.040)	(0.036)	(0.034)	(0.044)	(0.030)	(0.036)	(0.045)
Log number, Southern black migrants	0.188***	0.078***	0.197***	0.078***	0.055**	0.044*	0.055*
	(0.028)	(0.027)	(0.029)	(0.027)	(0.022)	(0.025)	(0.032)
Log population, 1960	0.956***	1.087***	1.131***	1.007***	0.950***	0.913***	1.285***
	(0.076)	(0.090)	(0.117)	(0.100)	(0.063)	(0.054)	(0.076)
Log population, 1970	0.960***	1.054***	1.151***	0.843***	0.922***	0.868***	1.267***
	(0.065)	(0.051)	(0.065)	(0.061)	(0.032)	(0.035)	(0.062)
Log population, 1980	0.975***	0.936***	1.201***	0.847***	0.893***	0.781***	1.452***
	(0.068)	(0.060)	(0.074)	(0.065)	(0.036)	(0.062)	(0.078)
Log population, 1990	0.933***	0.834***	1.123***	0.917***	0.900***	0.864***	1.254***
	(0.082)	(0.059)	(0.071)	(0.053)	(0.039)	(0.056)	(0.066)
Log population, 2000	0.961***	0.756***	1.143***	0.927***	0.925***	0.945***	1.206***
	(0.093)	(0.070)	(0.064)	(0.065)	(0.049)	(0.048)	(0.067)
Percent black, 1960	2.321***	3.083***	2.359***	3.148***	1.192***	-0.156	1.261***
	(0.388)	(0.520)	(0.462)	(0.574)	(0.385)	(0.411)	(0.452)
Percent black, 1970	1.648***	1.964***	1.164***	0.627**	0.632***	-0.294	1.229***
	(0.272)	(0.254)	(0.227)	(0.294)	(0.166)	(0.228)	(0.281)
Percent black, 1980	1.379***	1.390***	0.861***	0.511**	0.277*	-0.280	0.769***
	(0.207)	(0.172)	(0.198)	(0.255)	(0.153)	(0.264)	(0.270)
Percent black, 1990	1.288***	0.578**	0.366*	0.036	-0.079	-0.248	0.498
	(0.239)	(0.227)	(0.203)	(0.230)	(0.172)	(0.311)	(0.311)
Percent black, 2000	1.456***	0.126	0.018	-0.326	-0.096	-0.739***	0.769***
	(0.243)	(0.256)	(0.255)	(0.207)	(0.189)	(0.241)	(0.262)
Percent female, 1960	0.242	1.452	-3.222	0.063	3.388	1.374	1.031
	(3.407)	(3.658)	(4.176)	(4.124)	(2.816)	(2.076)	(3.236)
Percent female, 1970	3.612*	4.249*	1.644	-3.202	1.401	0.901	2.085
	(2.050)	(2.285)	(2.332)	(2.974)	(1.537)	(1.412)	(2.669)
Percent female, 1980	0.607	0.668	0.657	-4.436	3.927**	-0.842	4.002
	(2.133)	(2.833)	(2.780)	(3.050)	(1.938)	(2.258)	(3.559)

Table A.7: The Effect of Social Connectedness on Crime, 1960-2009, Results for All Explanatory Variables

	Dependent variable: Number of offenses reported to police						
	Murder (1)	Rape (2)	Robbery (3)	Assault (4)	Burglary (5)	Larceny (6)	Motor Vehicle Theft (7)
Percent female, 1990	-5.433**	-0.834	-0.291	-1.489	1.076	-1.322	3.778
	(2.760)	(2.924)	(3.308)	(2.375)	(2.211)	(2.246)	(3.911)
Percent female, 2000	4.053	-0.389	-1.803	2.341	-2.511	-1.030	-3.326
	(3.746)	(2.664)	(3.099)	(2.325)	(2.173)	(2.108)	(3.098)
Percent age 5-17, 1960	4.090	-12.179**	6.624	-4.568	-2.561	-9.611**	1.920
	(5.280)	(5.210)	(6.683)	(6.893)	(4.229)	(4.067)	(4.623)
Percent age 18-64, 1960	1.442	-13.519***	5.041	-1.187	-5.166	-9.784***	0.784
	(3.648)	(4.149)	(4.145)	(4.876)	(3.185)	(2.912)	(3.284)
Percent age 65+, 1960	-0.897	-12.557***	2.215	-9.096**	-4.374	-8.573***	-4.108
	(3.238)	(3.909)	(4.772)	(4.348)	(3.030)	(2.617)	(3.310)
Percent age 5-17, 1970	-5.454*	-11.591***	-7.378**	-9.470**	-5.736***	-5.050**	-1.159
	(3.152)	(2.967)	(3.103)	(4.491)	(2.037)	(2.304)	(3.276)
Percent age 18-64, 1970	-2.513	-7.947***	-3.592	-9.527**	-6.683***	-5.284***	2.039
	(2.814)	(2.631)	(2.636)	(4.310)	(1.820)	(2.035)	(2.734)
Percent age 65+, 1970	-4.309*	-10.748***	-5.395**	-6.652**	-5.116***	-4.239**	-2.523
	(2.517)	(2.359)	(2.459)	(3.169)	(1.668)	(1.705)	(2.685)
Percent age 5-17, 1980	-12.343***	-13.613***	-8.390**	-16.949***	-9.971***	-2.246	7.411*
	(3.438)	(3.245)	(4.121)	(4.793)	(2.607)	(4.333)	(4.480)
Percent age 18-64, 1980	-11.264***	-10.875***	-6.944**	-14.628***	-8.401***	-2.193	9.454***
	(2.666)	(2.486)	(3.176)	(3.460)	(1.877)	(2.546)	(3.444)
Percent age 65+, 1980	-8.755***	-10.386***	-5.146	-10.542***	-7.288***	-0.331	6.087
	(2.787)	(2.754)	(3.397)	(3.800)	(1.944)	(3.987)	(3.892)
Percent age 5-17, 1990	-17.106***	-13.983***	-11.102***	-8.701**	-9.031***	0.635	-1.025
	(4.958)	(4.238)	(3.917)	(4.136)	(2.896)	(3.216)	(4.776)
Percent age 18-64, 1990	-16.182***	-10.698***	-8.172***	-8.045***	-10.217***	-0.423	0.254
	(3.203)	(2.952)	(2.739)	(2.998)	(2.090)	(2.428)	(3.189)
Percent age 65+, 1990	-12.205***	-10.496***	-7.097**	-6.718**	-7.550***	1.355	-0.501
	(3.600)	(3.203)	(2.835)	(3.101)	(2.104)	(2.216)	(3.452)
Percent age 5-17, 2000	-5.758	-12.822**	-4.488	-1.759	1.393	0.675	4.214
	(6.000)	(5.300)	(4.663)	(4.404)	(4.506)	(4.279)	(5.517)

Table A.7: The Effect of Social Connectedness on Crime, 1960-2009, Results for All Explanatory Variables

	Dependent variable: Number of offenses reported to police						
	Murder (1)	Rape (2)	Robbery (3)	Assault (4)	Burglary (5)	Larceny (6)	Motor Vehicle Theft (7)
Percent age 18-64, 2000	-7.346	-9.093**	-4.664	-3.497	0.375	0.722	3.622
	(4.501)	(4.131)	(3.687)	(3.429)	(3.476)	(3.318)	(4.367)
Percent age 65+, 2000	-6.160	-10.015**	-4.328	-1.760	0.662	0.826	2.470
	(4.962)	(4.067)	(3.564)	(3.415)	(3.538)	(3.329)	(4.131)
Percent 25+ with HS, 1960	-0.868	1.218	0.845	0.763	0.147	-0.392	-1.020
	(0.697)	(0.903)	(0.954)	(0.889)	(0.637)	(0.585)	(0.850)
Percent 25+ with HS, 1970	-2.151***	-0.171	-1.111**	-2.481***	-0.388	0.363	-2.797***
	(0.642)	(0.536)	(0.549)	(0.620)	(0.363)	(0.403)	(0.742)
Percent 25+ with HS, 1980	-1.743***	-0.198	-0.871	-1.017	-1.246***	-1.141*	0.140
	(0.638)	(0.540)	(0.698)	(0.675)	(0.358)	(0.628)	(0.696)
Percent 25+ with HS, 1990	-1.328**	1.471***	-0.997**	1.791***	0.968***	0.967**	-0.546
	(0.557)	(0.518)	(0.469)	(0.486)	(0.354)	(0.470)	(0.574)
Percent 25+ with HS, 2000	-1.221*	2.296***	-0.902	1.986***	1.283**	1.393***	-0.792
	(0.662)	(0.671)	(0.627)	(0.575)	(0.503)	(0.398)	(0.636)
Percent 25+ with college, 1960	-1.294	0.480	-2.807**	-1.669	1.207	2.721***	-0.344
	(1.065)	(1.353)	(1.361)	(1.536)	(0.939)	(0.718)	(1.344)
Percent 25+ with college, 1970	-0.994	0.518	-1.033	1.884***	1.430***	1.484***	0.322
	(0.791)	(0.578)	(0.693)	(0.667)	(0.366)	(0.395)	(0.912)
Percent 25+ with college, 1980	-0.774	-0.182	-1.066*	0.483	0.376	1.343***	-3.154***
	(0.637)	(0.554)	(0.637)	(0.664)	(0.394)	(0.426)	(0.868)
Percent 25+ with college, 1990	-0.721	-0.797**	-0.573	-0.810**	0.481	0.743**	-1.976***
	(0.492)	(0.400)	(0.385)	(0.355)	(0.326)	(0.294)	(0.603)
Percent 25+ with college, 2000	-0.517	-1.181**	-0.563	-0.562	-0.317	0.190	-2.108***
	(0.607)	(0.511)	(0.510)	(0.429)	(0.410)	(0.354)	(0.630)
Log area, square miles, 1960	-0.056	0.011	-0.193**	-0.075	-0.003	-0.007	-0.223***
	(0.067)	(0.081)	(0.079)	(0.086)	(0.056)	(0.046)	(0.069)
Log area, square miles, 1970	-0.043	0.039	-0.227***	0.045	0.031	0.055*	-0.228***
	(0.065)	(0.051)	(0.060)	(0.059)	(0.029)	(0.031)	(0.053)
Log area, square miles, 1980	0.003	0.151***	-0.243***	0.067	0.090***	0.161***	-0.320***
	(0.059)	(0.051)	(0.064)	(0.057)	(0.031)	(0.053)	(0.065)

Table A.7: The Effect of Social Connectedness on Crime, 1960-2009, Results for All Explanatory Variables

	Dependent variable: Number of offenses reported to police						
	Murder (1)	Rape (2)	Robbery (3)	Assault (4)	Burglary (5)	Larceny (6)	Motor Vehicle Theft (7)
Log area, square miles, 1990	0.018	0.166***	-0.227***	0.031	0.065*	0.068	-0.114**
	(0.067)	(0.054)	(0.064)	(0.047)	(0.038)	(0.049)	(0.054)
Log area, square miles, 2000	-0.037	0.188***	-0.271***	0.028	0.060	0.010	-0.078
	(0.082)	(0.063)	(0.068)	(0.056)	(0.049)	(0.044)	(0.055)
Log median family income, 1960	-1.556***	-1.825***	-1.254*	-1.638**	-1.264***	-0.668*	-0.291
	(0.531)	(0.685)	(0.659)	(0.736)	(0.418)	(0.353)	(0.535)
Log median family income, 1970	-0.498	-1.231***	-0.432	-0.030	-0.848***	-0.951***	0.784*
	(0.342)	(0.307)	(0.398)	(0.371)	(0.209)	(0.203)	(0.403)
Log median family income, 1980	-0.714***	-1.302***	-0.872***	-0.339	-0.272	-0.842***	0.321
	(0.275)	(0.251)	(0.335)	(0.346)	(0.206)	(0.229)	(0.373)
Log median family income, 1990	-0.731**	-1.607***	-1.024***	-1.272***	-1.226***	-1.565***	-0.225
	(0.322)	(0.250)	(0.306)	(0.247)	(0.220)	(0.207)	(0.400)
Log median family income, 2000	-1.116***	-1.870***	-0.939***	-1.619***	-1.099***	-1.094***	-0.515**
	(0.223)	(0.216)	(0.198)	(0.183)	(0.193)	(0.177)	(0.237)
Unemployment rate, 1960	-1.338	-1.160	4.738	0.107	1.527	2.859	1.992
	(2.228)	(3.311)	(3.644)	(3.507)	(2.250)	(2.050)	(2.668)
Unemployment rate, 1970	-1.122	-0.995	0.769	2.839	0.167	0.271	-1.071
	(1.940)	(2.011)	(2.475)	(2.192)	(1.419)	(1.366)	(2.486)
Unemployment rate, 1980	1.209	2.203*	-1.063	4.740***	1.798*	3.109***	-1.511
	(1.194)	(1.152)	(1.341)	(1.788)	(0.925)	(1.015)	(1.910)
Unemployment rate, 1990	6.273***	2.061	2.984*	1.595	3.266**	-0.715	2.555
	(2.158)	(1.820)	(1.544)	(1.679)	(1.461)	(1.664)	(2.655)
Unemployment rate, 2000	-1.197	-1.046	-1.831	1.182	2.050*	2.584**	-1.325
	(1.716)	(1.437)	(1.449)	(0.981)	(1.236)	(1.139)	(1.085)
Labor force participation rate, 1960	4.933**	6.183**	7.873***	5.922***	4.896***	3.227***	3.771**
	(2.069)	(2.701)	(2.448)	(2.030)	(1.789)	(1.024)	(1.799)
Labor force participation rate, 1970	0.725	1.086	2.181*	2.685*	1.801***	1.110	-0.468
	(1.241)	(1.040)	(1.153)	(1.384)	(0.636)	(0.719)	(1.061)
Labor force participation rate, 1980	2.280**	3.117***	2.569*	3.350**	1.639**	3.763***	-3.449**
	(1.086)	(1.094)	(1.323)	(1.479)	(0.680)	(1.176)	(1.554)

Table A.7: The Effect of Social Connectedness on Crime, 1960-2009, Results for All Explanatory Variables

	Dependent variable: Number of offenses reported to police						
	Murder (1)	Rape (2)	Robbery (3)	Assault (4)	Burglary (5)	Larceny (6)	Motor Vehicle Theft (7)
Labor force participation rate, 1990	4.163***	2.719***	3.950***	1.572*	3.034***	3.234***	1.025
	(1.188)	(1.049)	(1.359)	(0.926)	(0.934)	(0.897)	(1.497)
Labor force participation rate, 2000	1.109**	1.188***	1.574***	1.310***	0.490	1.182***	0.803
	(0.548)	(0.401)	(0.488)	(0.378)	(0.410)	(0.358)	(0.523)
Manufacturing emp. share, 1960	-0.262	0.017	0.451	1.016*	-0.001	-0.132	-0.447
	(0.338)	(0.477)	(0.479)	(0.523)	(0.319)	(0.256)	(0.381)
Manufacturing emp. share, 1970	-0.043	0.015	-0.166	0.139	0.080	-0.032	-0.315
	(0.317)	(0.307)	(0.297)	(0.436)	(0.208)	(0.229)	(0.298)
Manufacturing emp. share, 1980	0.183	-0.005	-0.514	-0.027	-0.447*	-0.788**	-0.020
	(0.337)	(0.309)	(0.371)	(0.455)	(0.269)	(0.377)	(0.490)
Manufacturing emp. share, 1990	-0.624	0.157	-0.831*	0.469	-0.245	-0.342	-0.863
	(0.463)	(0.477)	(0.499)	(0.432)	(0.376)	(0.394)	(0.667)
Manufacturing emp. share, 2000	-0.966*	0.751	-1.357***	0.364	-0.365	-0.270	-1.086**
	(0.514)	(0.461)	(0.498)	(0.424)	(0.420)	(0.355)	(0.540)
State fixed effects	x	x	x	x	x	x	x
Pseudo R2	0.812	0.869	0.945	0.926	0.945	0.939	0.930
N (city-years)	19,254	18,058	19,254	19,254	19,254	19,254	19,254
Cities	479	479	479	479	479	479	479

Notes: See note to Table 3.

Sources: FBI UCR, Duke SSA/Medicare data, Census city data book

Table A.8: Negative Selection of Southern Black Migrants into Connected Destinations, 1960-1970

Sample:	Men and Women			Men			Women		
Dependent variable:	Years of Schooling (1)	Log Income (2)	Log Income (3)	Years of Schooling (4)	Log Income (5)	Log Income (6)	Years of Schooling (7)	Log Income (8)	Log Income (9)
Panel A: Selection into state of residence									
Share of migrants from birth state in state of residence	-1.594***	-0.107***	-0.041	-1.768***	-0.058**	0.019	-1.516***	-0.025	0.090*
	(0.154)	(0.031)	(0.030)	(0.176)	(0.022)	(0.019)	(0.152)	(0.051)	(0.052)
Years of schooling			0.041***			0.044***			0.076***
			(0.002)			(0.001)			(0.005)
N	97,132	77,760	77,760	45,187	42,960	42,960	51,945	34,800	34,800
R2	0.080	0.084	0.099	0.082	0.120	0.147	0.082	0.110	0.150
Panel B: Selection into metropolitan area of residence									
Share of migrants from birth state in metro of residence	-1.990***	-0.182***	-0.108**	-2.057***	-0.118***	-0.036	-1.995***	-0.154***	-0.002
	(0.117)	(0.044)	(0.044)	(0.108)	(0.035)	(0.036)	(0.154)	(0.057)	(0.059)
Years of schooling			0.036***			0.039***			0.070***
			(0.002)			(0.001)			(0.006)
N	66,359	52,958	52,958	30,533	29,201	29,201	35,826	23,757	23,757
R2	0.084	0.070	0.081	0.086	0.102	0.125	0.088	0.096	0.131
Quartic in age	x	x	x	x	x	x	x	x	x
Birth year fixed effects	x	x	x	x	x	x	x	x	x
Birth state fixed effects	x	x	x	x	x	x	x	x	x
State/metro of residence fixed effects	x	x	x	x	x	x	x	x	x
Survey year fixed effects	x	x	x	x	x	x	x	x	x

Notes: Sample limited to African Americans born in the South from 1916-1936 who are living in the North, Midwest, or West regions. Standard errors, clustered by state of residence, are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Sources: 1960 and 1970 Census IPUMS

Table A.9: The Relationship between Social Connectedness, the Number of Migrants, and the Share of Migrants that Chose their Destination Because of Social Interactions

	Dependent variable: Log HHI, Southern black migrants			
	(1)	(2)	(3)	(4)
Log number, Southern black migrants	-0.448***		-0.646***	-0.648***
	(0.014)		(0.022)	(0.024)
Share of migrants that chose destination because of social interactions		-2.537***	2.815***	2.884***
		(0.280)	(0.233)	(0.266)
State fixed effects				x
R2	0.726	0.198	0.828	0.843
N (cities)	479	479	479	479

Notes: We estimate the share of migrants that chose their destination because of social interactions using a structural model, as described in Appendix D.
Sources: Duke SSA/Medicare data

Table A.10: The Effect of Social Connectedness on Crime, 1960-2009, Additional Robustness Checks

	Dependent variable: Number of offenses reported to police						
	Murder	Rape	Robbery	Assault	Burglary	Larceny	Motor Vehicle Theft
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Including large cities with most extensive measurement error in crime							
Log HHI, Southern	-0.162***	-0.152***	-0.183***	-0.184***	-0.128***	-0.106***	-0.227***
black migrants	(0.036)	(0.037)	(0.038)	(0.043)	(0.027)	(0.031)	(0.038)
Pseudo R2	0.934	0.921	0.983	0.947	0.973	0.969	0.968
N (city-years)	19,543	18,324	19,543	19,543	19,543	19,543	19,543
Cities	485	485	485	485	485	485	485
Panel B: Negative binomial model							
Log HHI, Southern	-0.111***	-0.055*	-0.133***	-0.093***	-0.050*	-0.048*	-0.112***
black migrants	(0.032)	(0.031)	(0.038)	(0.034)	(0.027)	(0.029)	(0.041)
Pseudo R2	0.294	0.226	0.195	0.147	0.154	0.130	0.154
N (city-years) 19,254	18,058	19,254	19,254	19,254	19,254	19,254	
Cities	479	479	479	479	479	479	479
Panel C: Drop observations if dependent variable is below 1/6 or above 6 times city mean							
Log HHI, Southern	-0.102***	-0.040	-0.184***	-0.130***	-0.095***	-0.063*	-0.112**
black migrants	(0.039)	(0.037)	(0.034)	(0.045)	(0.030)	(0.037)	(0.044)
Pseudo R2	0.807	0.876	0.948	0.918	0.949	0.944	0.933
N (city-years)	15,590	16,052	18,207	15,567	19,112	19,115	19,011
Cities	478	479	479	479	479	479	479
Panel D: Drop observations if dependent variable is below 1/6 or above 6 times city median							
Log HHI, Southern	-0.134***	-0.045	-0.183***	-0.133***	-0.095***	-0.063*	-0.113**
black migrants	(0.039)	(0.037)	(0.034)	(0.045)	(0.030)	(0.037)	(0.044)
Pseudo R2	0.814	0.878	0.948	0.919	0.949	0.944	0.933
N (city-years)	16,109	16,156	18,230	15,570	19,105	19,093	19,050
Cities	479	478	479	479	479	479	479
Panel E: Measure HHI using birth county to destination city population flows							
Log HHI, Southern	-0.143***	-0.039	-0.169***	-0.121***	-0.076***	-0.060	-0.093**
black migrants	(0.040)	(0.034)	(0.036)	(0.040)	(0.030)	(0.038)	(0.044)
Pseudo R2	0.812	0.869	0.945	0.926	0.944	0.938	0.930
N (city-years)	19,254	18,058	19,254	19,254	19,254	19,254	19,254
Cities	479	479	479	479	479	479	479

Notes: In Panel B, we estimate a negative binomial model instead of equation (11). For Panels C and D, we construct mean and median number of crimes for each city from 1960-2009. Regressions include the same covariates used in Table 3. Standard errors, clustered at the city level, are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Sources: FBI UCR, Duke SSA/Medicare data, Census city data book

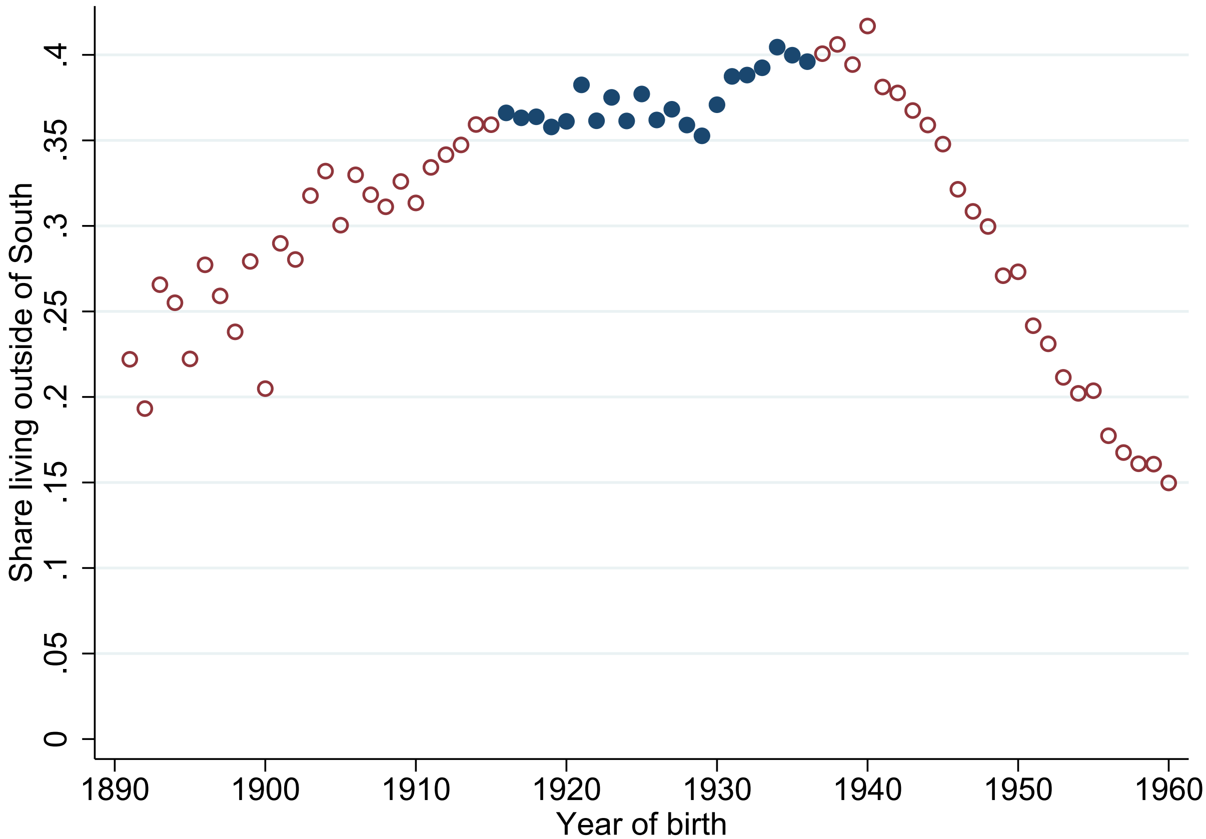
Table A.11: The Effect of Social Connectedness on Crime, 2000-2009, by Predicted Crimes

	Dependent variable: Number of offenses reported to police						
	Murder (1)	Rape (2)	Robbery (3)	Assault (4)	Burglary (5)	Larceny (6)	Motor Vehicle Theft (7)
All Cities	-0.077	0.086	-0.055	-0.161***	-0.022	-0.038	-0.045
	(0.078)	(0.063)	(0.051)	(0.052)	(0.043)	(0.041)	(0.057)
Below Median Predicted Crimes	-0.021	0.124	-0.065	0.042	0.043	-0.013	0.195**
	(0.095)	(0.084)	(0.071)	(0.074)	(0.066)	(0.055)	(0.079)
Above Median Predicted Crimes	-0.089	0.095	-0.068	-0.209***	-0.046	-0.046	-0.049
	(0.083)	(0.077)	(0.060)	(0.064)	(0.050)	(0.046)	(0.070)

Notes: Table displays estimates of equation (11). Regressions include the same covariates used in Table 3. To generate the predicted number of crimes for each city, we estimate equation (11) using data from 1995-1999, replacing state-year fixed effects with state-specific linear time trends. We then predict the number of crimes with these coefficients and covariates from 2000-2009, using the average value of log HHI and log number of migrants for all cities when generating the prediction. We divide the sample on the basis of average number of predicted crimes per year from 2000-2009, and we estimate regressions using data from 2000-2009. Standard errors, clustered at the city level, are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

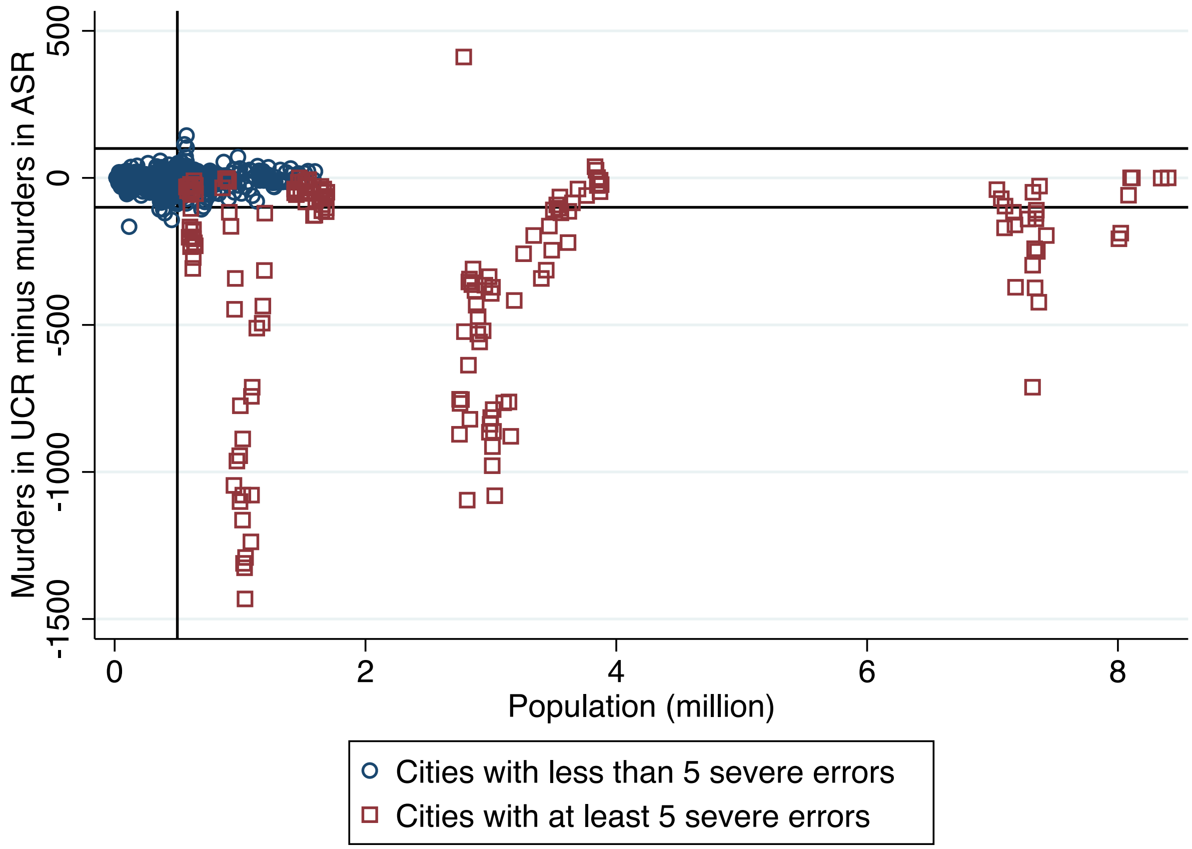
Sources: FBI UCR, Duke SSA/Medicare data, Census city data book

Figure A.1: Share of African Americans Born in the South Living Outside the South in Their 40s



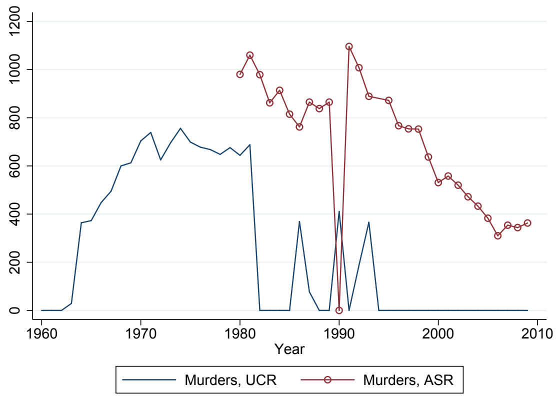
Notes: Sample contains African Americans from the eleven former Confederate states. For individuals born from 1891-1900, we measure their location using the 1900 Census. For individuals born from 1901-1910, we use the 1910 Census, and so forth. The shaded circles correspond to individuals born from 1916-1936, who comprise our sample from the Duke SSA/Medicare data.
Source: IPUMS Census data, 1940-2000

Figure A.2: Comparison of Murders Cleared by Arrest in FBI UCR versus ASR Data

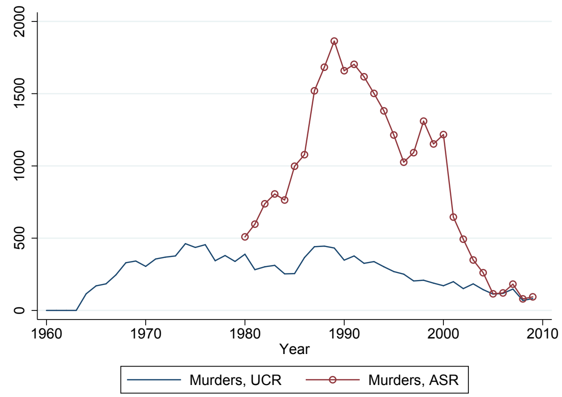


Notes: We classify a "severe error" as a year in which the absolute value of the difference between murders in the UCR and ASR data is at least 100. The six cities with at least five severe errors are Chicago, Detroit, Los Angeles, Milwaukee, New York, and Philadelphia.
Source: FBI UCR and ASR data

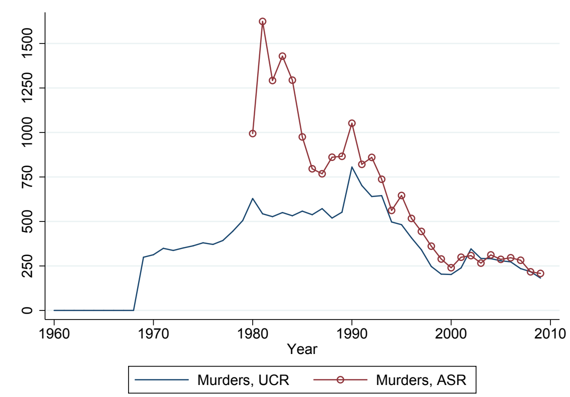
Figure A.3: The Relationship Between the Number of Murders Cleared by Arrest in UCR and ASR Data, 1960-2009



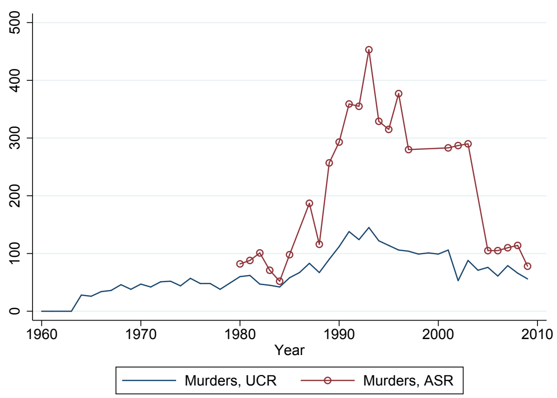
(a) Chicago



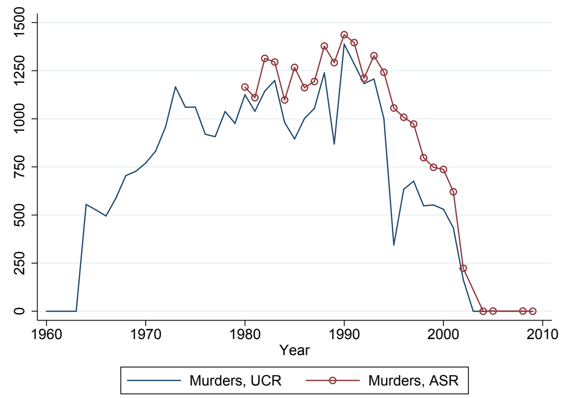
(b) Detroit



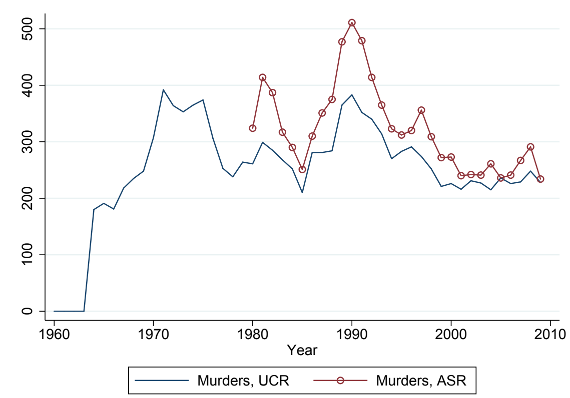
(c) Los Angeles



(d) Milwaukee



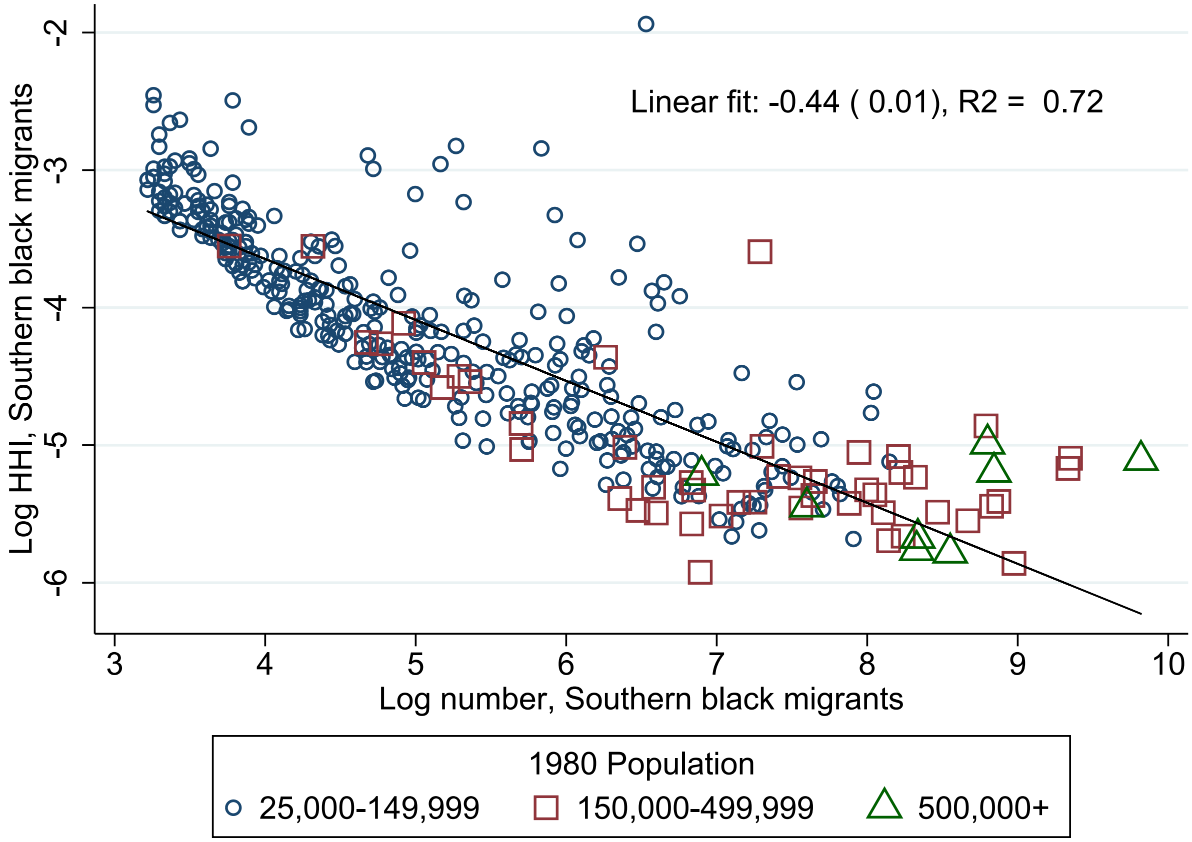
(e) New York



(f) Philadelphia

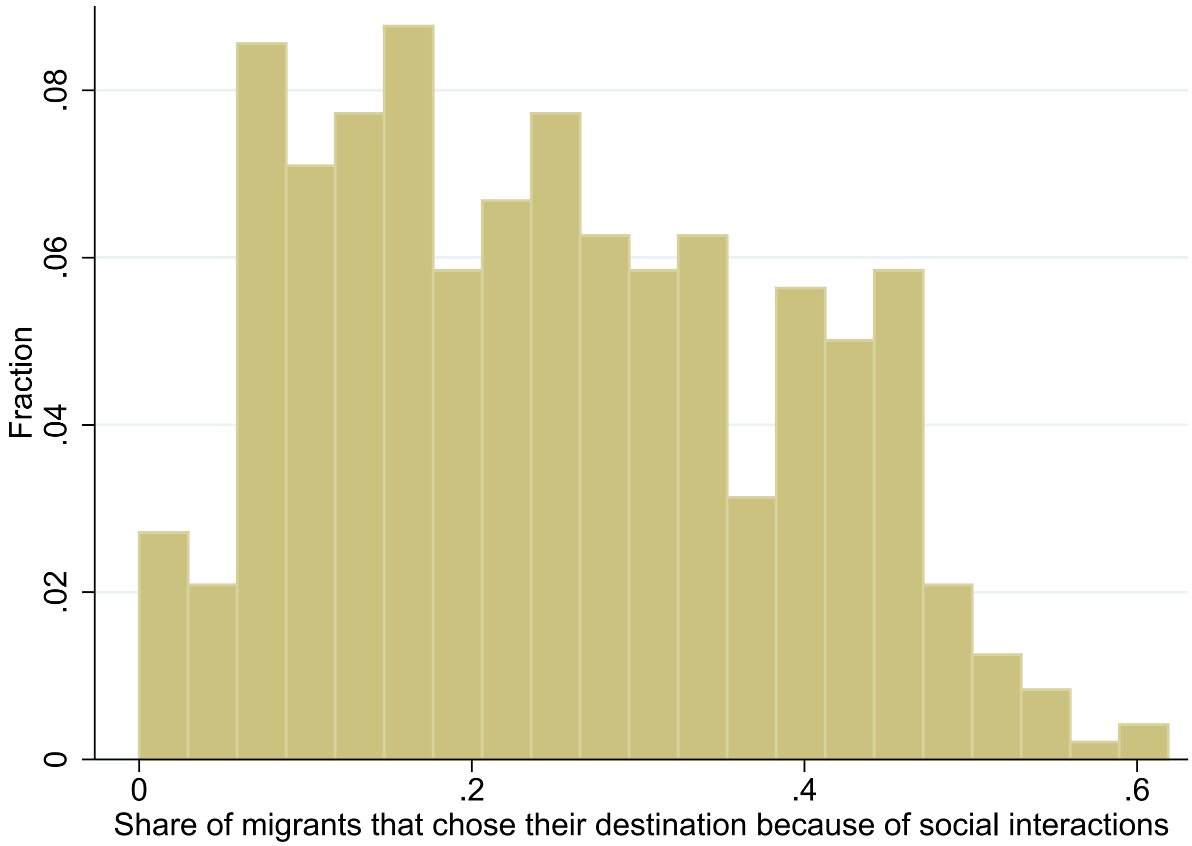
Notes: ASR data are first available in 1980. The cities in Appendix Figure A.3 are those for which the absolute value of the difference in murders between UCR and ASR data is at least 100 for at least five years.
Source: FBI UCR and ASR data

Figure A.4: The Relationship between Social Connectedness and the Number of Southern Black Migrants



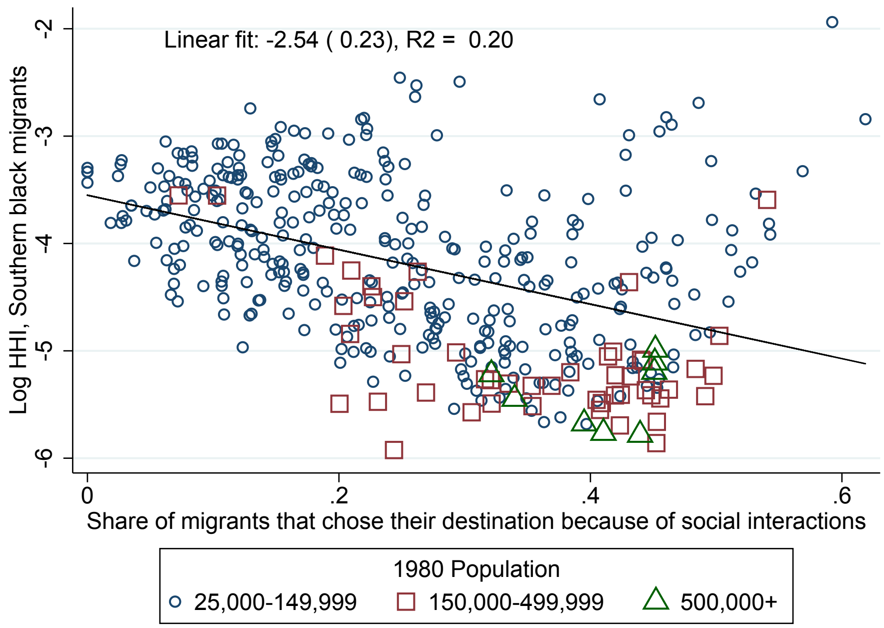
Notes: Figure contains 412 cities.
Source: Duke SSA/Medicare data

Figure A.5: Share of Migrants that Chose their Destination Because of Social Interactions

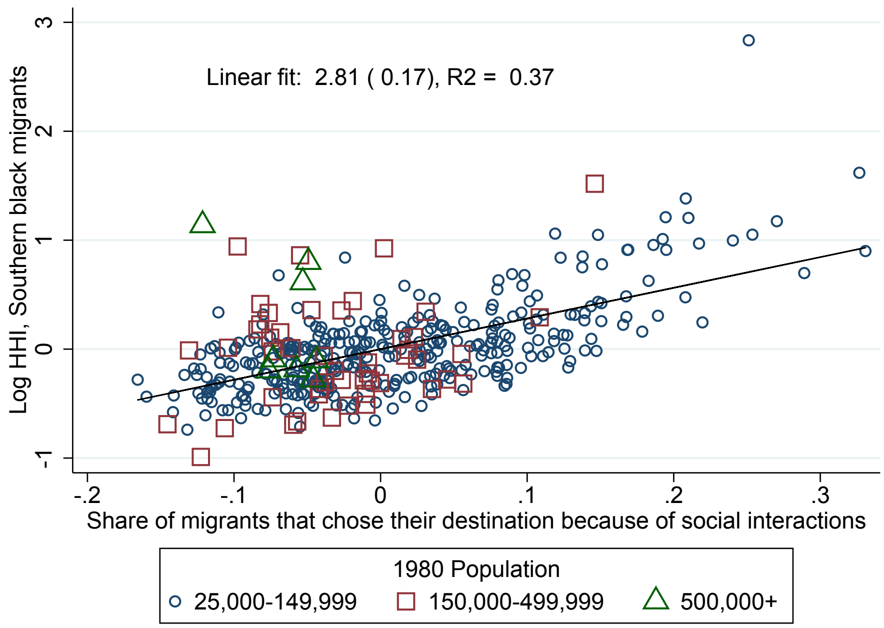


Notes: We estimate the share of migrants that chose their destination because of social interactions using a structural model, as described in Appendix D.
Source: Duke SSA/Medicare data

Figure A.6: The Relationship between Social Connectedness and the Share of Migrants that Chose their Destination Because of Social Interactions



(a) Unconditional



(b) Conditional on Log Number, Southern Black Migrants

Notes: We estimate the share of migrants that chose their destination because of social interactions using a structural model, as described in Appendix D. Panel B plots the residuals from regressing log HHI and the share of migrants that chose their destination because of social interactions on the log number of migrants.
Source: Duke SSA/Medicare data