UNMAKING THE SELF-MADE MAN:
INTERGENERATIONAL MOBILITY IN THE U.S. REVISITED

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UNMAKING THE SELF-MADE MAN:
INTERGENERATIONAL MOBILITY IN THE U.S. REVISITED

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Abstract

This paper investigates income transmission dynamics in the United States by providing estimates for intergenerational mobility-- the degree to which a parent's socioeconomic status affects that of their dependents. Using data from the University of Minnesota's Integrated Public Use Microdata Series project (IPUMS), we calculate mobility estimates for Americans born in 1910 and 1980 using county level data. We find that across time, population subset, and model specification, there is strong evidence of spatial dependence in the data. This implies that traditional OLS model specifications used to estimate intergenerational mobility are not appropriate and instead, spatial econometric models should be employed. We also offer further support for an overall decrease in U.S. mobility over time and relatively lower levels of mobility for racial minorities compared to that of whites. Additionally, we discuss the discrepancies in intergenerational mobility across gender lines by examining the relatively unexplored role of women in income transmission relationships.

KEYWORDS: (Intergenerational mobility, Spatial Effects, Gender)
JEL CODES: (J62, C21, J16)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED
UNAUTHORIZED AID ON THIS THESIS

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1. Introduction

Ideology rooted in the Declaration of Independence's proclamation of equality, de Tocqueville's early observations of American life, and the mystique of frontier exploration, popularly characterizes the United States as a highly mobile society-- a society where an individual's success is independent of their socioeconomic conditions at birth (Kamp, 2009). Socioeconomic mobility is measured by intergenerational income elasticity (IGE), or the extent to which a child's future success depends on that of their parents. Despite the United States' image as "the land of opportunity," recent IGE estimates indicate that the U.S. is not only substantially less mobile than popular perception suggests but also less mobile than other developed countries (Black & Devereux, 2010). For example, Solon's (1999) widely cited estimates imply that, for a family living at the poverty line, it will take 75 years (3 generations) for their descendents to earn within 5% of the national average income (Mazumder, 2005). Other studies argue that even this prediction is modest-- 125 to 150 years (5 to 6 generations) is more accurate (Mazumder, 2005).[1] Exacerbating low mobility levels, there is evidence that mobility is declining over time, with large drops after the 1940s and 1980s (Aaronson & Mazumder, 2008; Black & Devereux, 2010).

While empirical evidence that challenges notions of the American Dream have heightened interest in mobility research, few studies address differences in mobility between population subsets and geographic space (Black & Devereux, 2010). This oversight could have adverse policy implications. For example, if racial minorities are

[1] These timelines are based on Mazumder's (2005) calculations which compare the implications of his 0.6 IGE estimate to Solon's (1999) 0.4 IGE figure. He assumes a family living at the poverty line is earning 75% of the national average income.

relatively immobile, legislative programs that allocate funding to predominately white areas, even if they are poor, could exacerbate concentrated poverty instead of alleviating it. To ignore these potential discrepancies in mobility between peoples and space can lead to the adoption of one-size-fits-all poverty reduction plans, which are often vague and ineffective.

This paper investigates intergenerational mobility dynamics over time, space, and population subset by estimating IGEs for 1910-1940 and 1980-2010 for both men and women in addition to specifications conditioned on race. To address possible spatial autocorrelation in mobility data hinted at in Chetty et al.'s (2014) work and augmented by strong evidence of spatial correlation in related poverty literature (Rupasingha & Goetz, 2007), we use county level data that allows one to account for potential spatial patterns through spatial econometric models.

The vast majority of mobility studies are largely concerned with men, excluding potential discrepancies in the transmission of socioeconomic status across gender (Chadwick & Solon, 2002). Research that has considered women primarily examines the effect of father's income on his daughter's income (Torche, 2015). Father-daughter IGEs are usually smaller in magnitude than male IGEs, implying that a father's socioeconomic status affects their son's economic outcomes more than their daughter's (Black & Devereux, 2010; Jantti et al., 2006; Olivetti & Paserman, 2014). Only a few studies find IGE estimates for mothers (Torche, 2015). Of these estimates, mother IGEs tend to be lower than father IGEs. This indicates that mothers exert less influence on their dependents' future socioeconomic status than the children's fathers (Ermisch & Francesconi, 2002).

Recent work also illustrates significant local variation in intergenerational mobility within the United States (Chetty et al., 2014). This variation appears to be non-random, resulting in clusters of low and high mobility areas (Chetty et al., 2014). In particular, the pockets of low mobility in the Mississippi Delta, the South Eastern Atlantic coast, and East North Central Midwest, all geographically align with clusters of high poverty widely acknowledged in poverty literature (Rupasingha & Goetz, 2007). The potential presence of spatial autocorrelation in mobility data, suggested by the visible geographic clustering of mobility, calls for a more thorough analysis of the discrepancies in mobility manifested across space and their casual mechanisms.

Using data from the University of Minnesota's Integrated Public Use Microdata Series project (IPUMS), we have five key findings. First, there is strong evidence of spatial dependence in the data across time, model specification, and population subset. This empirically confirms the spatial patterns suggested by Chetty et al.'s (2014) work. The existence of spatial autocorrelation means that traditional OLS estimation methods are not appropriate because in the presence of non-random, correlated observations, OLS-estimated coefficients are biased and inefficient. In the future, spatial econometric models that account for spatial autocorrelation between observations should be used. Second, this paper provides further support for an overall decrease in mobility over time. For the full samples including all sexes and races, IGEs range from 0.117 to 0.160 in 1910-1940 and 0.517 to 0.649 in 1980-2010. Third, non-whites are less mobile than whites. This also implies that racial minorities have lower levels of upward mobility because minorities earn less on average and there are relatively few non-whites at the extreme upper tail of the income distribution (Fry & Kochhar, 2014). In other words, minorities are staying poor while whites are relatively more mobile. Fourth, we find that a father's income influences their son's future income more than their daughter's, a finding in line with previous studies' father-daughter IGE estimates (Black & Devereux, 2010; Bratsberg et al., 2007; Hirvonen, 2008; Jantti et al., 2006; Österberg, 2000). Lastly, while a mother's income has essentially no effect on their son's future socioeconomic status, it is significant in determining that of their daughter. Moreover, this maternal influence on daughter earnings grows substantially over time, likely due to women's increased penetration of the labor market.

2. Theoretical Background

The canonical theoretical reference for economic studies on intergenerational mobility is Becker's (1981) model. This model describes a utility-maximizing parent who can either invest in their child or purchase consumer goods (Becker, 1981). A child's future success is impacted by this investment, in addition to the parent's natural endowments and environmental effects independent of parental influence (Becker, 1981). This section outlines the ways in which a child's socioeconomic status depends on these factors, relying heavily on this model and Goldberger's (1989) subsequent analysis of Becker's (1981) work.

First, parents impact their dependents' earnings through altruistic investments in their children. Therefore, parents can allocate their wealth *X* between their personal consumption *C* and investment in their children *I*:

$$X = C + I \tag{1}$$

By investing in their child, primarily through commitments towards higher educational attainment, parents can increase their child's future earnings. The dependent's permanent income *Y* is defined by:

$$Y = (1 + r)I + E \tag{2}$$

where *r* is the rate of return on the parent's investment and *E* captures the child's "luckiness" in the market (Becker, 1981). Parents gain utility through their own consumption and their child's future wellbeing or permanent income (Becker, 1981). Assuming a Cobb-Douglas utility function (Goldberger, 1989), the parent's utility *U* is:

$$U = \alpha logY + (1 - \alpha)logC \tag{3}$$

Here, α is bounded between 1 and 0. This displays the importance the parent places on their own consumption relative to their child's future wealth (Goldberger, 1989). Parents maximize their utility (3) subject to equations (1) and (2). This gives the parent's optimal allocation of income between consumption and investment:

$$C = (1 - \alpha)X + \frac{(1 - \alpha)E}{(1 + r)} \tag{4}$$

$$I = \alpha X - \frac{(1 - \alpha)E}{(1 + r)} \tag{5}$$

Substituting (5) into (2), the dependent's income becomes:

$$Y = \alpha(1 + r)X + \alpha E \tag{6}$$

Therefore, the parent's income and their investments in their child directly affect their dependent's future income. The parameters α and *r* outline the nature of that investment. α defines the portion of income spent on the dependent while *r* reflects the effectiveness of the investment and consequently, the likelihood to invest.

If *b* equals $\alpha(1+r)$, equation (6) can be rewritten as:

$$Y = bX + \alpha E \tag{7}$$

Equation (7) is the theoretical analog of the empirical equation (9) in the subsequent section where *b* is the intergenerational elasticity. This coefficient quantifies the direct influence a parent's income has on their child's future income.

In addition to direct investment, parents influence their dependents' income through endowments. Becker (1981) splits a child's "luckiness" *E* into endowments *e* and market luck *u*:

$$E = e + u \tag{8}$$

Endowments are all the child's innate abilities and capital received from their parents at birth at no cost (Goldberger, 1989). Parental endowments can be divided into two subcategories: wealth and genetic inheritance.

First, socioeconomic status can be transmitted through wealth, or the lack thereof. While bequeaths are visibly important for the upper end of the income distribution, most individuals are relatively unaffected by the inheritance of wealth (Bowles & Gintis, 2002). Mulligan (1997) estimates that only 2-4% of estates between 1960-1995 were subject to inheritance taxes. Accordingly, while wealth impacts intergenerational mobility for the affluent by preserving socioeconomic elite membership, it is not a significant mechanism for the middle and lower classes.

Second, parents can provide genetic endowments through the transmission of both cognitive skills, non-cognitive skills, and demographic non-skill traits. There is a growing body of literature devoted to the inheritance of cognitive skills that find a strong, positive correlation between parent and child IQs, ranging from 0.42-0.72 (Bouchard & McGue, 1981; Plomin et al., 2013). Furthermore, the range between identical twins' incomes is much smaller than that for fraternal twins (Bowles & Gintis, 2002). This suggests that genetic effects may be important factors in determining earnings. Inheriting cognitive skills affects income through a direct and an indirect effect. Directly, cognitive skills are positively correlated with higher individual incomes even after allowing for differences in education (Hanushek & Woessmann, 2008). The indirect effect is manifested through educational attainment. For example, inheriting a high IQ corresponds to more advanced educational attainment-- which is again a strong predictor of income (Bowles & Gintis, 2002). Empirically, this indirect effect is accounted for with the EDUC control described in the following section. This control identifies the percent of people with at least a high school degree in each county.

Non-cognitive skills, such as dispositions and personality traits, are also forms of genetic endowments. Often non-cognitive skills are deciding factors in exchanges that directly affect one's economic status, like employment contracts and loan agreements. Accordingly, intergenerational endowments of non-cognitive skills can affect a child's economic opportunities and their future income. This transmission is empirically evidenced. For example, fatalism, social maladjustment, and occupational self-direction in parents are likely to be inherited by those parents' dependents (Groves, 2005; Kohn, 1969).

Lastly, parents genetically endow their dependents with demographic, non-skill traits that are influential in determining income. Of these traits, race is arguably the most significant. It is well documented that racial minorities experience lower levels of mobility compared to whites (Bowles & Gintis, 2002). Hertz (2002) finds that while 43% of white children born into the top income quartile remain in that socioeconomic position, the same is true for only 9% of black children. Overall, black children from the bottom of the income distribution experience less upward mobility and black children born into the top rungs of the socioeconomic ladder face more downward mobility than white children (Hertz, 2002). Hertz (2002) estimates that these racial differences account for 0.07 of the intergenerational correlation between parent and dependent earnings. Because of this, the control RACE is included in the following empirical analysis. This variable indicates the percent change in number of Caucasians living in each county. In addition to race, other genetically inherited non-skill traits, such as height and obesity, can influence income. For example, tall men and thin women have higher incomes on average than short men and obese women (Bowles & Gintis, 2002). We consider discrepancies in the importance of such non-skill traits between men and women through a control for gender in the later empirical equations. Controlling for gender is also important because men earn more than women on average (U.S. Bureau of Labor Statistics, 2014). Accordingly, the variable MALE documents the percent change in the number of males in each county.

In addition to parental investments and endowments, a dependent's income is also influenced by environmental effects. Neighborhood effects on low levels of mobility and the persistence of poverty are well documented (Rupasingha & Goetz, 2007). Environmental characteristics, such as labor market tightness, social capital levels, health conditions, political climate, and the degree of ethnic diversity, are all significant determinants of an individual's socioeconomic status (Rupasingha & Goetz, 2007). High levels of negative neighborhood externalities can create geographical poverty traps, in which environmental conditions depress mobility irrespective of an individual's characteristics. In other words, “an otherwise identical household living in a better-endowed area enjoys a rising standard of living” while the other household remains poor (Jalan & Ravallion, 2002). The degree of urbanization is a particularly important environmental factor. Suburban counties on average have much lower poverty rates and higher economic mobility levels than their rural counterparts (Rupasingha & Goetz, 2007). Principally during periods of industrialization, labor demand and employment growth rates tend to increase in cities, improving the prospects of urban dwellers over those living in rural areas (Levernier et al., 2000). The URBAN control addresses these issues in the model by including the percent change in the number of people living in an urban area.

An individual can avoid adverse environmental effects or capitalize on positive neighborhood externalities by moving. Outward migration may benefit those living in a destitute area, but can also concentrate poverty for those left behind. Migrants however do not necessarily move to better areas. In fact, some studies suggest that the poor tend to move to other poverty traps instead of to more prosperous areas (Nord, 1998). For those living in immigrant-receiving areas, the effect of immigration is unclear. Despite popular belief, there is little evidence that immigrants have an adverse effect on native wages

(Friedberg & Hunt, 1995) with the exception of Borjas's (2003) results. Thus, to account for the role migration might play for both migrants and natives, a control for the county level net migration rate MIGRATE is included in the empirical model.

3. Empirical Methodology

Intergenerational mobility studies are interested in how much a parent's socioeconomic status affects their dependent's socioeconomic prospects (Becker, 1981). Empirically, this is measured by the degree to which the dependent's income or occupation depends on that of their parents.

Prior research indicates that spatial dependence may be a problem in mobility data. Using tax data Chetty et al. (2014) finds significant variation in intergenerational mobility across the U.S. at the commuting zone level. This variation appears to have clustering patterns. There are large pockets of low mobility in the Mississippi Delta, the South Eastern Atlantic coast, and East North Central Midwest and high mobility in the Northeast and Western half of the country. More broadly, there is a large body of poverty literature that finds strong evidence of spatial autocorrelation within Census data at the county level (Rupasingha & Goetz, 2007). Spatial autocorrelation means that variables and their residuals are correlated with each other solely because of the observations' geographic proximity (Cliff & Ord, 1981). More illustratively, a person living next to a poor area is likely poorer than an otherwise identical person living next to a rich area. Although distinct, poverty and mobility studies are inherently related. While poverty rates provide a snapshot of socioeconomic condition during one time period, intergenerational mobility can help link snapshots by describing poverty dynamics over time. Because these two strands of literature are interconnected, and this paper also uses

Census data, it is logical to suppose the spatial dependence problems present in measuring poverty exist in mobility estimates. The Moran's I test is employed to detect the presence of spatial dependence. The Moran's Is, displayed in Table 3, illustrate that there is strong evidence of spatial autocorrelation in all but one model specification. This reaffirms Chetty's (2014) and poverty literature's prior findings (Rupasingha & Goetz, 2007).

Traditional methods measure intergenerational mobility on the individual level (Black & Devereux, 2010). The canonical specification for individual data makes it difficult to study the role of space in mobility studies because individual level datasets, like the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY), often lack sufficient geographic data. While the Census provides data on individuals including geographic information, it does not include enough linkages between parent and dependent to constitute a large enough sample. To circumvent this problem, this paper averages individual income data across continental United States counties to create "artificial" average parents and dependents for each county. This method also allows one to address the possibility of spatial patterns in mobility through spatial econometric methods.

This paper estimates the following model:

$$\ln(Y_i) = \alpha + \beta \ln(X_i) + \gamma MALE_i + \delta WHITE_i + \zeta URBAN_i + \eta EDUC_i + \theta MIGRATE_i + \varepsilon_i, \qquad \varepsilon_i \sim N(0, \sigma^2) \tag{9}$$

in which Y_i is the artificial, average dependent income and X_i is artificial, average parent income for each county. Briefly stated, X_i is the average income for parents (people aged 30-40 years old) in year 1 and Y_i is the average income for people who are children in year 1 (who are 0-10 years old in year 1 and 30-40 in year 2) for each county. Variables MALE, WHITE, URBAN, EDUC, and MIGRATE are controls (Olivetti & Paserman, 2013; Rupasingha & Goetz, 2007). They indicate the percent change in the number of males, the percent change in the number of Caucasians, the percent of people living in an urban area, the percent of people with at least a high school degree, and the net migration rate for each county respectively.

Mobility studies are primarily interested in the coefficient β because β is the marginal effect of parent's income on their dependent's income. Accordingly, (1-β) is a value for intergenerational mobility because this expresses the extent to which one's future success (or lack thereof) is not dependent on their parent's socioeconomic condition. Because this model is estimated using natural log earnings for both the parent and the child, the estimate β is an elasticity, specifically the intergenerational elasticity. IGE estimates typically range from 0 to 1 (Goldberger, 1989). If β equals 1, there is no economic mobility-- children will remain in the same socioeconomic position as their parents. Conversely, an IGE of 0 indicates perfect economic mobility. This means that a parent's socioeconomic status has no impact on their child's outcomes and every child, regardless of their socioeconomic position at birth, is equally likely to be on any rung of the socioeconomic ladder. After Solon's (1999) work the benchmark IGE in American mobility literature is 0.4. This implies that a 10 percent increase in parent income corresponds to a 4 percent increase in child's income. Because IGE is a measure of relative mobility, it is difficult to make normative statements describing the "ideal" IGE value. While lower IGEs indicate higher mobility, higher mobility does not necessarily correspond to upward movement. High mobility could mean that the poor are getting richer at the expense of the rich becoming poorer.

In addition to finding the IGE for the full samples, this paper estimates IGEs for six subsets based on race and sex. Because IGE values could differ across population subset, it is informative to estimate IGEs for these groups separately. For example, a father's socioeconomic position could wield greater influence than a mother's on his children's future opportunities because men are typically the primary household earner. Estimating separate IGEs allows one to distinguish between the potentially varying magnitude of income transmission effects and their corresponding explanatory mechanisms. Accordingly, this paper considers six regression subsets described in Appendix C: father-son, father-daughter, mother-son, mother-daughter, and two race conditioned subsets. While racial minority and father-son IGEs are well documented, research considering IGEs for the remaining three subsets is limited. Prior studies disproportionately focus on men (Chadwick & Solon, 2002). As a result, this paper's female subsets are relatively unique because there are few father-daughter IGE estimates and only a handful of studies that include mothers (Torche, 2015). To look at changes in mobility over time, the IGEs for these subsets are estimated for both 1940 and 2010.

To account for the possibility of spatial autocorrelation, this paper employs both spatial error and spatial lag model specifications that build off of equation (9). The spatial error model is appropriate when spatial dependence acts through the disturbance term *u*:

$$\ln(Y_i) = \alpha + \beta \ln(X_i) + \gamma MALE_i + \delta WHITE_i + \zeta URBAN_i + \eta EDUC_i + \theta MIGRATE_i + u, \tag{10}$$

$$u = \lambda W u + \varepsilon_i, \qquad \varepsilon_i \sim N(0, \sigma^2 I_n)$$

Here, W is a spatial weight matrix and λ is the scalar spatial error coefficient. The spatial lag specification is an autoregressive model in which the spatial dependence works through a spatial lag in log child earnings.

$$\ln(Y_i) = \alpha + pW\ln(Y_i) + \beta\ln(X_i) + \gamma MALE_i + \delta WHITE_i + \zeta URBAN_i + \eta EDUC_i + \theta MIGRATE_i + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2 I_n) \tag{11}$$

In the above equation, p is the scalar spatial autoregressive parameter.

Both of these models rely on the construction of a spatial weight matrix W. A spatial weight matrix is an n x n matrix with elements w_{ij}, that provides information about the structure of spatial relationships between observations, indicating if county i and county j are neighbors or spatially close. This paper utilizes two kinds of spatial weight matrices: queen contiguity and inverse distance matrices. The queen contiguity and inverse distance matrices are each used with both the spatial error and spatial lag models (Cliff & Ord, 1981). A queen contiguity matrix is binary- w_{ij} equals 1 if county i and county j share a border or a vertex or equals 0 if the counties are not neighbors. The matrix is then row-standardized, in which every element in each row is divided by the sum of the row to create proportional weights in cases where some counties have more neighbors than others. The elements in an inverse distance spatial weight matrix, in contrast, equal simply $1/d$ between each county, where d is the distance between each county's centroid. This type of matrix epitomizes Tobler's (1970) first law of geography: "everything is related to everything else, but near things are more related than distant things." Again, this matrix is row standardized so that each element is the weighted average of its neighbor's values.

In the presence of spatial autocorrelation, the spatial error and spatial lag model specifications are econometrically more appropriate than OLS-based estimations. In order for OLS estimators to be unbiased and efficient, residuals must be independent and randomly distributed by the Gauss-Markov simple linear regression assumptions. Spatial autocorrelation violates this condition because residuals are correlated and not random. By including a spatial weight matrix, the spatial error and spatial lag models are able to account for dependence between observations because the matrix's off-diagonal elements represent the structure of each observation's relationships across space (Anselin, 2001). If spatial autocorrelation is manifested through a lagged dependent variable, estimations must address this endogeneity (Anselin, 2001). This can be accomplished through a spatial lag specified model. Conversely, using OLS in this case creates biased and inefficient parameters due to a simultaneity bias (Anselin, 2001). While spatial dependence acting through the disturbance term does not bias OLS estimators, it does result in inefficient coefficients and biased standard error classical estimators (Anselin, 2001). Hence, if spatial autocorrelation exists, spatial models are econometrically preferred to OLS estimations.

While we include both spatial lag and spatial error specifications, we focus on the spatial error results because the structure of spatial relationships in the data is uncertain. It is unclear whether spatial autocorrelation is endogenous or not. Moreover, spatial error models are principally used to correct for possible bias in estimates due to spatial autocorrelation whereas spatial lag models are usually employed to test the strength of that autocorrelation (Anselin, 2001). Because the former is our primary concern, the spatial error results dominant the remainder of this paper.

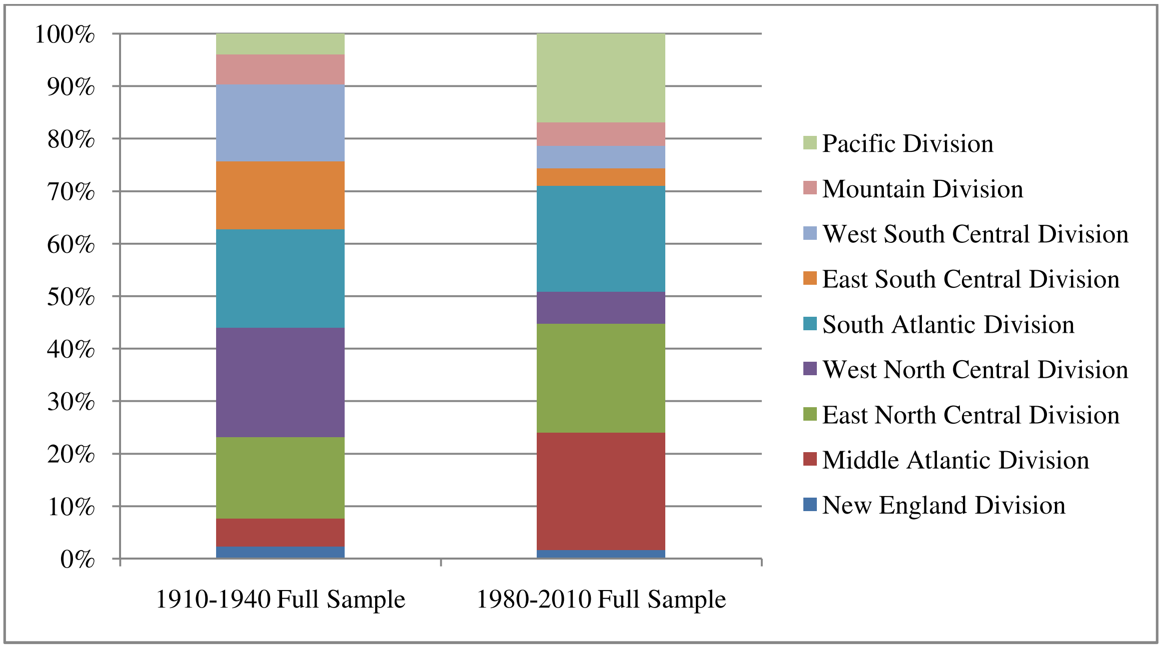
4. Data

Data for this paper is obtained from the University of Minnesota's Integrated Public Use Microdata Series project 1910, 1940, 1980, and 2010 Census data samples (Ruggles et al., 2010). For 1910, 1940, and 2010 the 1% sample is used, in which each observation represents approximately 100 people in the population. For 1980 the 5% sample is used, in which each observation represents 20 people in the population.

The 1910-1940 full sample includes 2,775 counties from every state in the continental United States, including the District of Columbia.[2] Because the IPUMS samples strive to be nationally representative of the U.S. population distribution, more counties are typically included for more populous states. For example, in the 1910-1940 full sample there are 197 Texas counties but only 7 counties from Nevada. Of the total 2,775, counties are dispersed fairly evenly between Census regional divisions, although the West North Central and South Atlantic divisions are slightly overrepresented while the New England and East North Central divisions are underrepresented. This is illustrated in Figure 1.

[2] See Appendix A for illustrative maps of the counties included in the full samples and regression subsets.

Figure 1: Percent of Represented Counties in Each Census Division



Source: Author's calculations using data from Ruggles et al., 2010

The 1980-2010 full sample includes 183 counties. Twenty states are not included in the sample. These are generally some of the least populous states. The distribution between Census regional divisions is not as equal as the distribution in the 1910-1940 full sample. Again, the New England Census division is underrepresented and the East North Central, Middle Atlantic, and South Atlantic divisions are significantly overrepresented.

Since individual income data is not available before 1940, the 1910-1940 subsets use a socioeconomic status measure based on occupation as a proxy for individual income. Although, this proxy cannot fully capture the differences in individual's income within an occupation, the practice of using occupational status instead of income has a long history in social sciences and has resulted in IGE estimates very close to those based on income data (Björklund & Jäntti, 1997; Olivetti & Paserman, 2013). Like Olivetti & Paserman (2013, 2014) and Abramitsky & Platt-Boustan (2012), this paper uses the *occscore* IPUMS variable as an income proxy. This variable describes the median total income of those within each occupation in 1950. For the 1980-2010 subset, the individual income variable *income* is used and then chained to 2010 dollars.

Because we create an artificial average parent and child for each county, calculating accurate average county income values is imperative. First, since IPUMS data consists of samples taken from the Census, each individual represents a particular number of people in the population. To account for varying numbers of represented individuals in each sample, the IPUMS *perwt* variable is included to create weighted income averages for each county. *Perwt* indicates how many people in the county population are represented by a given individual in the IPUMS sample. Second, averages are only representative given large enough county sample sizes. When regressions are limited to exclusively comprise of certain population subsets, such as solely females or non-whites, certain counties are left with only a few observations. Therefore, in the subset regressions, counties are included only if they contain 4 or 20% of the observations of the full samples.

Controls are also included for age to address earnings variance across the lifecycle and the resulting lifecycle bias in IGE estimates (Haider & Solon, 2006). Theoretically, IGEs should be estimated using measures of permanent income for the parent and the child. Because very few datasets have information on permanent income, previous studies use annual income at specific ages to proxy average yearly income. To limit lifecycle bias, it is optimal to measure earnings in the middle of the child and parent's working years- starting when the individual is in their early thirties (Haider & Solon, 2006). To reduce the attenuation bias over the earnings lifecycle, an average of the individual's earnings for at least 5 years is ideal (Mazumder, 2005). Accordingly, only people aged 30-40 years old are included in each year's sample.

Furthermore, in each data extract, controls for migration are incorporated because this methodology assumes that the representative average child and parent of each county have only resided in that said county. Thus, only those living in their birth state and in the same county, house, or Public Use Microdata Area (PUMA) in the last five years are included in each year's sample (from the *migrate5* IPUMS variable). The net county level migration rate from supplemental Census data and the University of Wisconsin is also added as a control to further curtail for migration effects (*County Population Change*, 2015; Winkler et al., 2013).

In addition to migration rates, each regression includes controls for the percent of people living in an urban area, the percent of people with a high school degree, and the percent change in number of males and whites. All of these variables are created using data from IPUMS samples (Ruggles et al., 2010) and a list of the variables included in each regression can be found in Appendix B.

Tables 1 and 2 display descriptive statistics for the 1910-1940 and 1980-2010 full samples respectively. In the 1910-1940 and the 1980-2010 periods, average county income increases from year 1 to year 2. In both periods, this is driven by an increase in income for the upper tail of the distribution because the minimum values stay relatively constant. This is particularly evident in 1980-2010: the maximum average county income almost doubles from 44,983.10 dollars in 1980 to 90,109.34 in 2010. While the variance in average county income remains constant in the 1910-1940 period, it swells significantly between 1980 and 2010. This rise in variance, combined with the increase in maximum income, supports recent data on growing income disparities in the U.S. Particularly since the 1970s , the spread of income is widening and the rich are getting richer while the poor are remaining poor (Cassidy, 2013).

Table 1: Descriptive Statistics for the 1910-1940 Full Sample

Variable	Mean	Std. Dev.	Min	Max
1910 avg. county income	1926	470.165	400	4941.147
1940 avg. county income	2066.15	471.57	400	5150
URBAN	0.238	0.251	0	1
MIGRATE	0.061	0.154	-0.314	2.803
EDUC	0.158	0.079	0	0.75
MALE	-0.024	0.128	-0.637	1
WHITE	0.025	0.116	-0.508	1

Table 2: Descriptive Statistics for the 1980-2010 Full Sample

Variable	Mean	Std. Dev.	Min	Max
1980 avg. county income	32501.2	4542.44	20646.8	44983.1
2010 avg. county income	39557.9	9992.49	20246.9	90109.34
URBAN	0.88	0.121	0.522	1
MIGRATE	0.033	0.08	-0.181	0.298
EDUC	0.66	0.06	0.451	0.774
MALE	0.004	0.026	-0.072	0.088
WHITE	-0.109	0.122	-0.712	0.287

In 1910-1940, the spread in the URBAN, MIGRATE, and WHITE variables (described in Table 1 above) are large. In combination, these could be illustrative of the Great Migration. Fleeing segregation, racism, and the Great Depression's depletion of jobs in the rural South, six million African Americans migrated to cities in the West and the urban Northeast and Midwest (Gregory, 2009). Thus, urban destination counties' population and the number of resident African Americans increases in this period, while rural Southern counties become relatively whiter and less populous, evidencing the large variance in the URBAN, MIGRATE, and WHITE variables.

In 1980-2010, the patterns in the control variables differ. First, the average percent of people with at least a high school education in each county increases substantially from 6.1% in 1940 to 66.0% in 2010. This could be driven by the broadening of access to education opportunities through legislation, like the G.I. Bill, the desegregation of public schools, among other reasons (Hilger, 2015). Second, the average county resident in 2010 is significantly more likely to live in an urban area than in 1940. In 1940, only 23.8% of average county residents lived in an urban area, compared to 88.0% in 2010. Furthermore, the spread in the percent of urban dwellers is notably smaller in 2010 than in 1940. Lastly, on average, counties are more racially diverse from 1980 to 2010. This is potentially due to the rise in mixed-race marriages and higher minority population growth rates (U.S. Census Bureau, 2012). However, there is a large variance in the WHITE variable. While the United States is becoming more diverse as a whole, geographic racial segregation has concurrently increased (Massey & Denton, 1993).

Overall, the presence of discrepancies over time and large variances in variables across counties, support the use of these controls in this paper's estimations. By including the aforementioned variables as controls, we can help alleviate the effects of these variables on IGE estimates.

5. Results and Discussion

Table 3 reports the intergenerational elasticity results for different model specifications and regression subsets.[3] It illustrates that IGE ranges from 0.021 to 0.331 in 1910-1940 and approximately 0 to 0.649 in 1980-2010. In other words, a 10% increase

[3] Descriptions of the regression codes used in the first column of Table 3 can be found in Appendix C.

in parent income corresponds to a 0.21- 3.31% increase in child income in 1940 and a 0-6.49% increase in 2010. This indicates that mobility was relatively high in the early 20th century and has dropped since then. These results are robust across model specification. IGE estimates using OLS or spatial models with different spatial weight matrices are very similar for each regression subset. Moreover, including the regression controls described in the previous section reduces IGE magnitude but does not change the direction of the coefficients or the patterns between subset elasticities significantly.[4] However, while the results are robust, it is important to note that very small differences in intergenerational elasticities have large practical implications. Mazumder (2005) calculates that it will take a family living at the poverty line 50-75 years longer to be within 5% of the national average income than if they lived in an area with an IGE only 0.2 lower.[5] Therefore, the substantial weight of these small differences underlines the importance of IGE estimate precision, and consequently, model specification choice.

[4] See Appendix D for IGE estimates without controls.
[5] Mazumder (2005) assumes a family living at the poverty line is earning 75% of the national average income and the IGEs in question are 0.4 compared to 0.6.

Table 3: Intergenerational Elasticities and Regression Diagnostics Across Spatial Model Specifications for 1910-9140 and 1980-2010

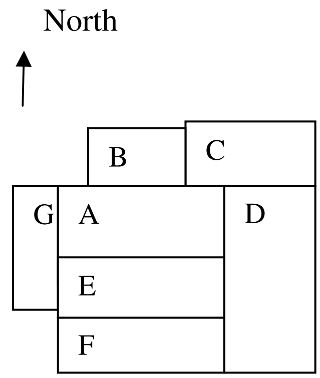
	Regression Coefficients					Regression Diagnostics		
Regression Code	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID	N	Moran's I, QC	Moran's I, ID
1040all	0.160***	0.117***	0.118***	0.128***	0.121***	2775	10.244***	39.165***
	(0.025)	(0.019)	(0.018)	(0.019)	(0.018)			
1040ff	0.228***	0.143***	0.125***	0.122***	0.100***	596	5.635***	15.502***
	(0.037)	(0.039)	(0.035)	(0.037)	(0.033)			
1040mf	0.331***	0.242***	0.260***	0.240***	0.249***	1219	8.852***	29.078***
	(0.060)	(0.058)	(0.056)	(0.058)	(0.056)			
1040fm	0.091***	0.064***	0.056***	0.057***	0.028**	820	8.762***	26.219***
	(0.015)	(0.014)	(0.014)	(0.015)	(0.013)			
1040mm	0.161***	0.138***	0.137***	0.143***	0.135***	2484	8.826***	31.872***
	(0.027)	(0.022)	(0.022)	(0.022)	(0.021)			
1040w	0.058	0.046	0.047	0.047	0.047	2680	6.566***	26.343***
	(0.024)	(0.019)	(0.019)	(0.019)	(0.019)			
1040nw	0.185***	0.165***	0.167***	0.166***	0.166***	554	3.294***	3.326***
	(0.068)	(0.050)	(0.048)	(0.050)	(0.049)			
8010all	0.624***	0.621***	0.517***	0.649***	0.558***	183	4.897***	12.527***
	(0.128)	(0.126)	(0.110)	(0.119)	(0.100)			
8010ff	0.497***	0.478***	0.393***	0.461***	0.387***	183	4.984***	8.837***
	(0.094)	(0.084)	(0.074)	(0.082)	(0.073)			
8010mf	0.149	0.179	0.140	0.252**	0.221**	183	5.464***	10.572***
	(0.119)	(0.112)	(0.010)	(0.111)	(0.096)			
8010fm	0.084	0.138	0.077	0.088	0.050	183	4.225***	10.496***
	(0.110)	(0.105)	(0.091)	(0.098)	(0.086)			
8010mm	0.562***	0.516***	0.484***	0.545***	0.514***	183	3.635***	10.805***
	(0.125)	(0.125)	(0.112)	(0.118)	(0.102)			
8010w	-0.053	0.046	-0.007	-0.025	-0.018	183	3.749***	10.146***
	(0.083)	(0.095)	(0.101)	(0.095)	(0.094)			
8010nw	0.135	0.134	0.128	0.108	0.101	150	0.320	1.666*
	(0.125)	(0.113)	(0.113)	(0.115)	(0.114)			

See Appendix C for regression code descriptions; ***, **, and * indicate significance at 1, 5, and 10% level respectively; All IGEs are jointly significant at the 1% level; QC or ID mean a queen contiguity or inverse distance spatial weight matrix was used respectively

Across time period, regression subset, and spatial weight matrix type, there is strong evidence of spatial dependence. This buttresses Chetty et al.'s (2014) findings that location matters: in which mobility has geographic discrepancies and clustering patterns. But while Chetty et al. (2014) imply the existence of spatial dependence, they do not explicitly model for it. If observations are spatially dependent, they are not independent and their error terms are correlated. These two points violate the Gauss-Markov assumptions that must be met in order for OLS estimations to be the best linear unbiased estimators of the coefficients. Therefore, in the presence of spatial dependence, OLS estimators are biased and inefficient. Consequently, calculating IGEs using spatial econometric models is more appropriate because these models explicitly account for spatial dependence and heterogeneity.

While this analysis tested spatial error and spatial lag models with both queen contiguity and inverse distance spatial weight matrices, the remainder of this paper focuses on the results from the inverse distance spatial weight spatial error model. A model using an inverse distance spatial weight matrix is better suited for modeling county data than models using contiguity matrices because county area varies greatly. For clusters of small counties, geographic borders are only marginally relevant. For example, in Figure 2 below, County F does not border County A but it is likely very similar to County E and the southern part of County D, both of which are counted as County A neighbors. A spatial regression model using a first degree contiguity matrix would assert independence between County A and F observations while an inverse distance matrix model accounts for varying degrees of "neighbor-ness" that is more suitable for groups of small counties.

Figure 2: County Map Example



Furthermore, a spatial error model is more appropriate than a spatial lag model because the structure of the spatial relationship is ambiguous; it is unclear if incomes from one county are directly affected by their neighboring counties' incomes. Moreover, spatial lag models are ideal when one's primary concern is evaluating the presence and strength of the spatial dependence (Anselin, 2001). In contrast, a spatial error model best when the focus is adjusting for the potential bias resulting from spatial autocorrelation due to the use of spatial data (Anselin, 2001). The latter is this paper's chief concern. Accordingly, using a spatial error model adjusts for spatial autocorrelation through unobservable features or omitted variables associated with location, without asserting correlation between dependent variables.

The discussion of the inverse distance spatial error results is structured as follows: To begin, the regressions typically included in existing literature are examined and contextualized--starting with the results for the full sample, race-conditioned IGEs, and the father-child subsets. Lastly, the results of the mother-son and mother-daughter subsets are discussed.

For the full sample, including all sexes and races, the IGE is 0.128 for 1910-1940 and 0.649 for 1980-2010. The full sample IGE for 1910-1940 is slightly lower than those found by previous studies while the IGE for 1980-2010 is greater than estimates in the literature. However, these elasticities reflect mobility trends evidenced in prior literature which document an overall decrease in mobility over time (Olivetti & Paserman, 2013; Olivetti & Paserman, 2014). After World War II, mobility drops significantly, stabilizes in the 1960s-1980s when panel data becomes available, (Hilger, 2015) and decreases again after 1980 (Aaronson & Mazumder, 2008). These results provide further evidence for the increasing concern over decreasing mobility in the United States. A decrease in mobility could help maintain, or contribute to, increasing economic inequality and the economic insulation of poor families in the lower end of the income distribution.

The patterns in IGEs conditioned on race are also consistent with existing literature (Kearney, 2006). In both time periods, the IGE for whites is very close to zero while non-white IGE is higher. Non-white IGE is 0.166 in 1910-1940 and 0.108 in 1980-2010. This indicates that intergenerational mobility is lower for demographic minorities but is increasing over time. Low mobility for racial minorities is well documented. Non-whites' ability to climb the socioeconomic ladder is deterred by racial discrimination in the labor market, the relocation of job opportunities outside of urban areas (Wilson, 1987), and racial and income segregation (Chetty et al., 2014).[6] Furthermore, lower mobility for non-whites is exacerbated by the fact that racial minorities are statistically lower income and very few minority households belong to the top earnings percentiles (Fry & Kochhar, 2014). This implies that, while whites may be upwardly mobile, minorities are likely staying relatively poor. Despite these factors, mobility increases, albeit slightly, for minorities over time. This could be driven by the increase in higher education options for minorities and, more generally, civil rights legislation that expanded opportunities for the historically marginalized (Hilger, 2015).

[6] Chetty et al. (2014) find that areas with a larger black population have greater levels of income segregation, which is strongly negatively correlated with upward mobility.

Like the full sample, the results for father-son IGE illustrate a decrease in mobility over time. Father-son IGE is 0.143 in 1910-1940 and 0.545 for 1980-2010. While the 1980-2010 father-son IGE is in line with existing studies, the IGE estimate for the 1910-1940 period is lower than that found previously (Hilger, 2015; Mazumder, 2005; Olivetti & Paserman, 2014).[7]

Furthermore, the IGEs between fathers and daughters mirror those previously estimated. In 1910-1940 father-daughter IGE is 0.240, rising only slightly to 0.252 in the 1980-2010 period. While the 1910-1940 IGE is lower than Olivetti & Paserman's (2013) figure, the 1980-2010 elasticity echoes that found by Jantti et al. (2006) in their cross-country comparison. The differences between father-son and father-daughter IGE estimates for 1980-2010 are also reflected in prior studies, in which father-daughter IGE is lower than father-son IGE. This could be largely driven by assortative mating and negative cross-wage effects (Bratsberg et al., 2007; Hirvonen, 2008; Holmlund, 2008; Jantti et al., 2006; Österberg, 2000). Women from wealthy families are more likely to marry high-earning men. After marrying wealthy men, these women choose to reduce their individual labor hours and consequently earn less individual income (Black & Devereux, 2010).The differences between father-son IGEs and father-daughter IGEs are significant because they illustrate that there may be divergent mechanisms underlying status transmission for men and women. Studies that group sons and daughters together broadly as "children" ignore the empirically evidenced possibility that the determinants of mobility are influenced by gender. Consequently, calculating intergenerational elasticities separately for men and women result in more precise estimates and shed light on differing casual mechanisms across gender lines.

[7] IGEs range from 0.300 to 0.476 for the 1940s and 0.300 to 0.600 for panel data estimates after 1960 (Hilger, 2015; Mazumder, 2005; Olivetti & Paserman, 2014).

The impact of maternal relationships on mobility has been relatively unexplored because of model and data limitations. The inclusion of women in IGE estimates is not only necessary for mollifying selection bias, but, as alluded to shortly above, it also enables comparison between the mechanisms driving potentially disparate maternal and paternal effects on a child's income. Accordingly, this is one of only a few papers to directly look at the effect of mothers' income on son and daughter earnings. From the inverse distance spatial error model, mothers' income has very little effect on sons' income in both time periods. Mother-son IGE is 0.057 in 1910-1940 and 0.088 in 1980-2010. These values are very similar to Fertig's (2003) estimates for the 1960s-1980s. Mothers' impact on daughters' earning are much more substantial. In 1910-1940, mother-daughter IGE is 0.122. This rises to 0.461 in the 1980-2010 period.

While these mother-daughter IGEs are greater than those estimated previously, the difference between maternal influence on son and daughter earnings is reflected in Ermisch & Francesconi's (2002) work and Anger & Heineck's (2010) research on cognitive skill transmission. Like this paper, Ermisch & Francesconi (2002) find that mother-daughter IGE is greater than mother-son IGE for the 1990s in Britain. This difference could be driven by the importance of gender-matching in mentoring relationships, in which individuals tend to seek role models of the same gender (Lockwood, 2006). Hence, sons' income is more affected by their fathers (father-son IGEs are greater than mother-son IGEs for both time periods) and daughters are more heavily influenced by their mothers.

Moreover, the rise in mother-daughter IGE over time could be explained by the growth in female labor force participation rates and greater diversity of roles for women beyond the household. As women's socioeconomic status grows significantly due to greater participation in the labor market, mothers' influence on children's earnings increases markedly. Considering the importance of gender-matched mentoring, this increase in influence would be especially impactful on daughters, particularly because women value gender-matched mentoring more than men (Lockwood, 2006). Ultimately, the combination of these effects are reflected in the rise in mother-daughter IGE over time.

In the 1910-1940 period, a father's income affects their children's earnings more than the mother's, regardless of the child's sex. In the 1980-2010 period, fathers' income remains more influential than mothers' earnings on sons' income but mother-daughter IGE is greater than father-daughter IGE. This change is not driven by a decrease in the father's influence on his daughter's income (because father-daughter IGE remains constant between 1910-2010), but rather by an increase in mother-daughter IGE. Arguably, the increase in women's socioeconomic status from 1910 to 2010 is the underlying explanatory factor behind these changes. In the 1910-1940 period, women's income constituted a small portion of household income. As a result, in 1910-1940 the father's earnings are much more indicative of the household's income and the children's original socioeconomic position. With growing economic opportunities, labor market presence, and female-headed families, by the 1980-2010 period women are more of equal earners in the household. Therefore, the rise in women's income and socioeconomic role within the household corresponds to an increase in maternal IGEs, particularly mother-daughter IGE.

By augmenting prior work with a new methodology, spatial IGE models, and mothers' influence on economic status transmission, this paper helps create a more illustrative picture of American mobility. These results illustrate that overall mobility has decreased over time but varies for different population subsets. Analyzing the extent to which economic status is transmitted across generations and differs between groups is important in the context of growing public discussion concerning poverty, equality of opportunity, and social welfare. Continued rises in intergenerational elasticity could lead to more persistent inequality that questions notions of the American Dream. As the literature turns to the causal determinants of mobility to address these problems, this paper's contributions and the mechanisms described above provide a better, more detailed analysis as the foundation for further work.

6. Conclusion

This paper investigates intergenerational mobility, or the degree to which parents' socioeconomic status affects that of their dependents. By employing county level data, we are able to account for geographic space more sufficiently than previous IGE studies. Accordingly, this paper finds that spatial correlation is a problem in mobility data, and consequently, OLS estimation methods are inappropriate. Using spatial econometric estimations that account for spatial dependence provides more accurate and precise results.

Specifically, we provide further evidence that overall mobility has decreased over time but trends and IGE magnitude differ by demographic subset. Racial minorities experience lower levels of mobility than whites. A father's socioeconomic position influences their son's opportunities more than their daughter's. Likewise, mothers' earnings have virtually no effect on their sons' future earnings but their impact on their daughters' earnings is significant and rises substantially over time. Because existing literature concerned with the role of women in mobility studies is very limited, the results for the father-daughter and mother-child subsets are particularly important contributions.

There are several avenues for future research that extend this paper's findings and address its limitations. First, we use U.S. counties to produce artificial average parents and dependents. This methodology assumes that counties are fairly homogenous and that county lines are appropriate divisions of similar people. To achieve heightened accuracy, and larger sample sizes, extending this methodology to Chetty et. al.'s (2014) tax data and creating average parents and dependents for every zip code could result in more precise IGE estimates. Second, due to the lack of county level historical data, the controls included in each regression are limited. Future inquiries should empirically consider additional variables, such as income inequality, residential segregation, industrialization, and the county's political environment. Lastly, more attention needs to be given to the role of women in intergenerational mobility. Given the relative lack of existing literature on this topic, principally regarding mothers, it is important to address the discrepancies between male and female mobility to better understand differing explanatory mechanisms for intergenerational income transmission.

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APPENDIX A[8]

Figure A.1: 1040all Counties

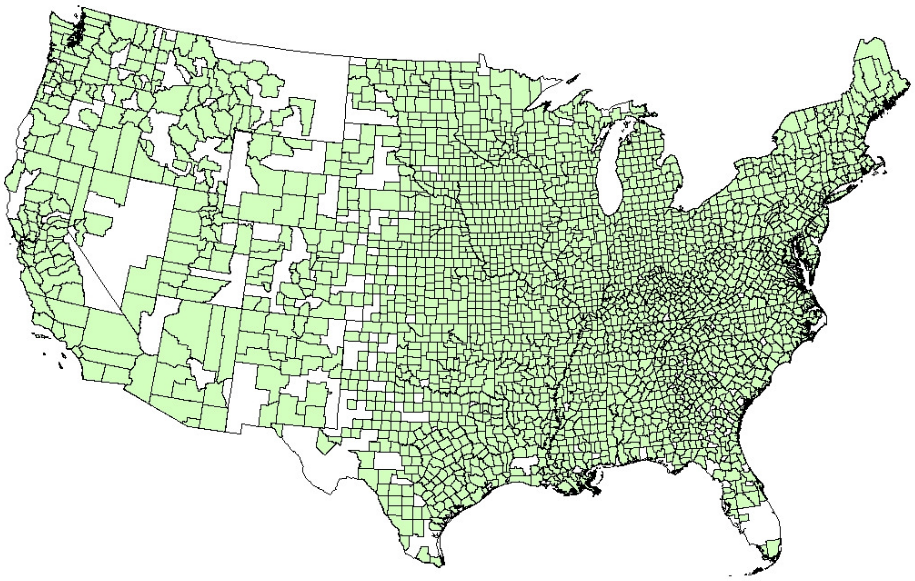
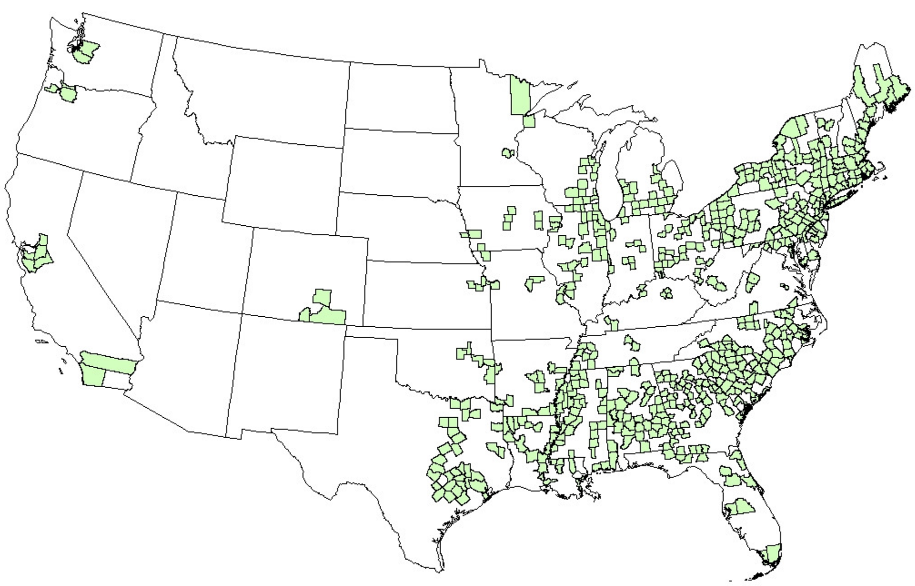


Figure A.2: 1040ff Counties



[8] Shaded counties are those included in each regression. See Appendix C for regression code descriptions.

Figure A.3: 1040mf Counties

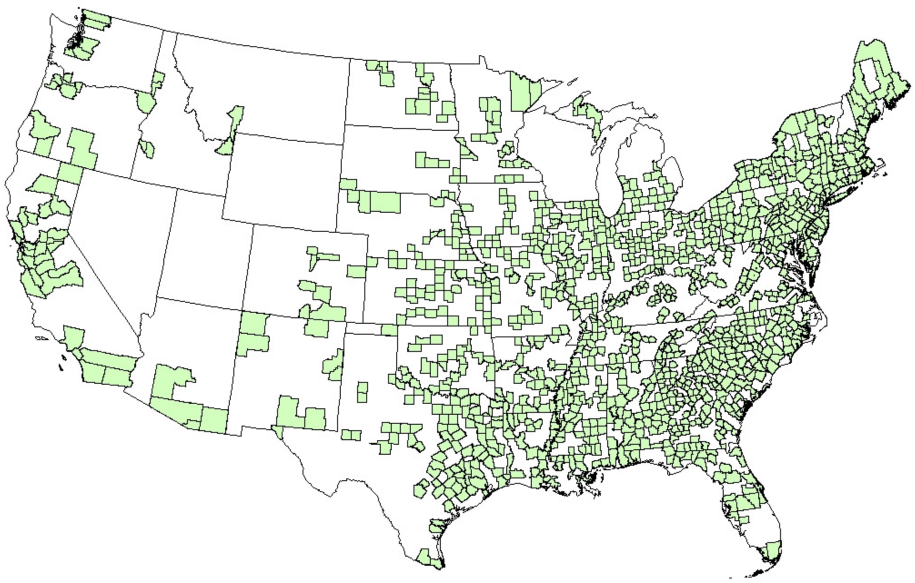


Figure A.4: 1040fm Counties

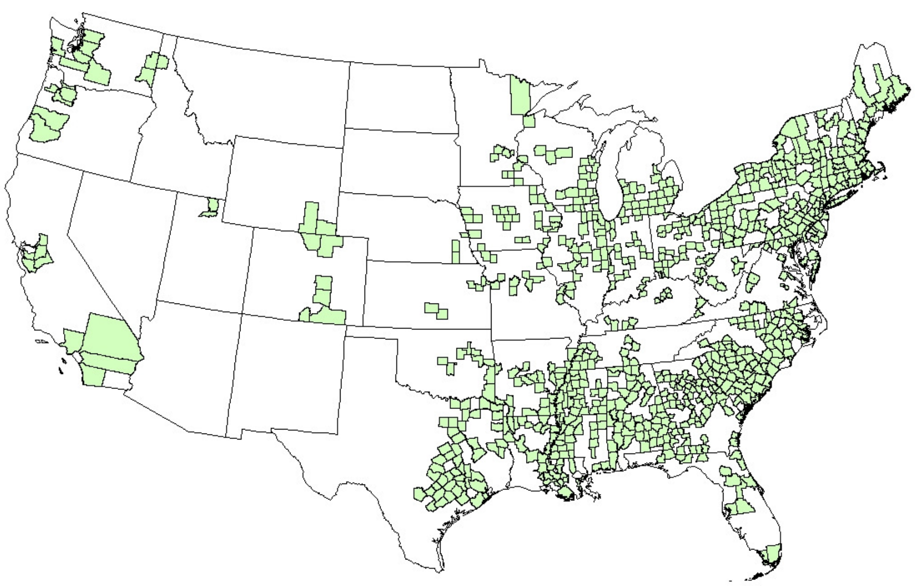


Figure A.5: 1040mm Counties

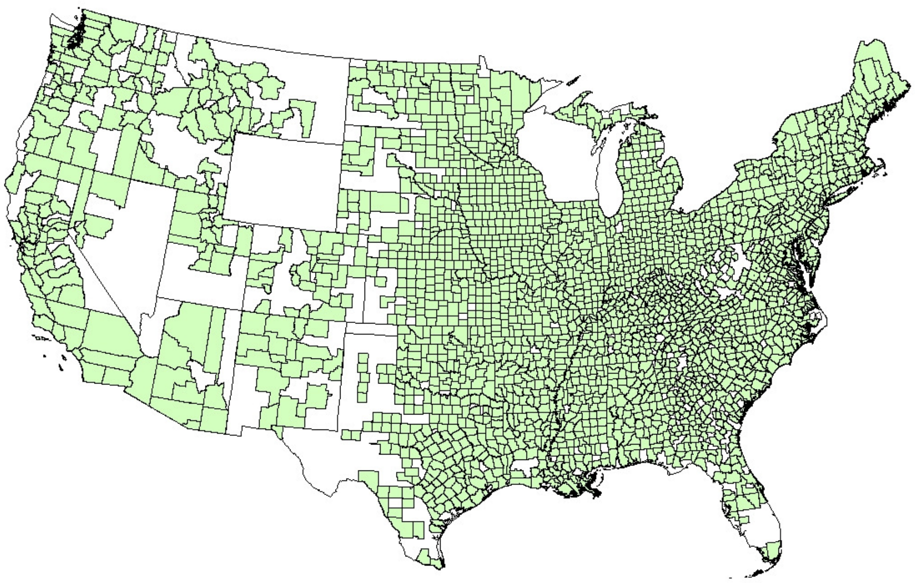


Figure A.6: 1040w Counties

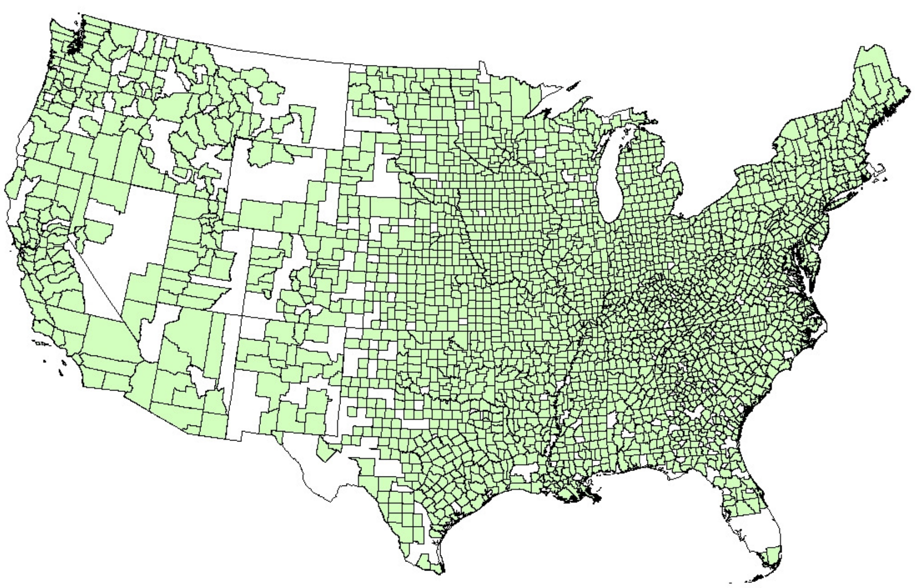


Figure A.7: 1040nw Counties

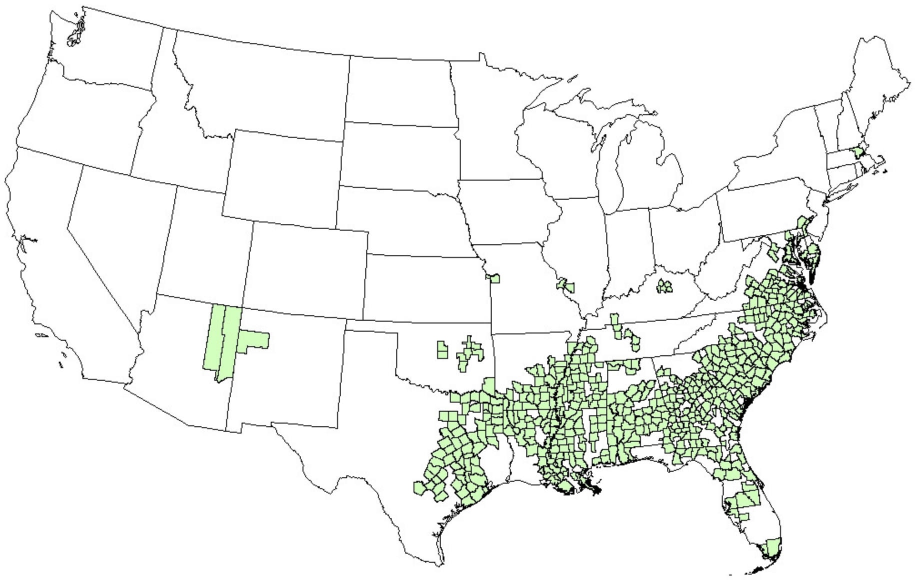


Figure A.8: 8010all, 8010ff, 8010mf, 8010fm, 8010mm, and 8010w Counties

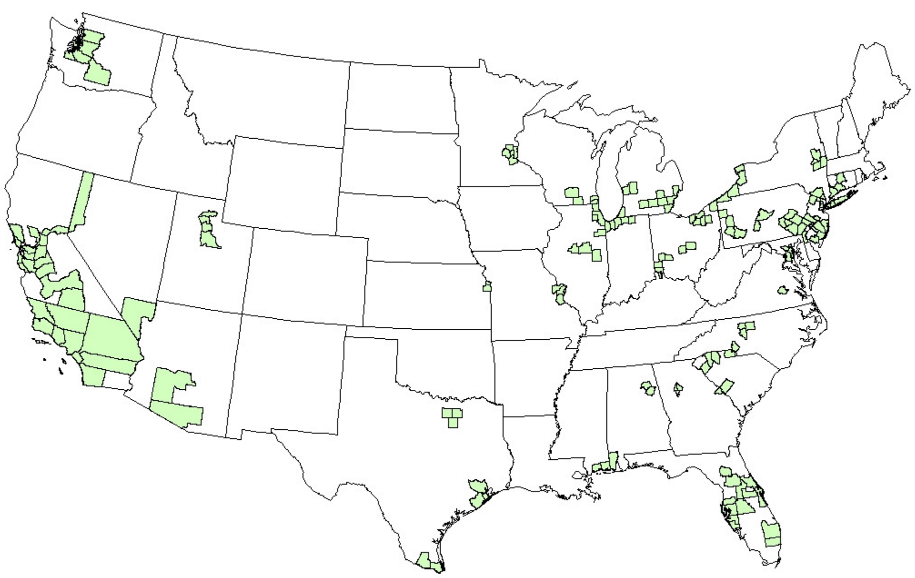
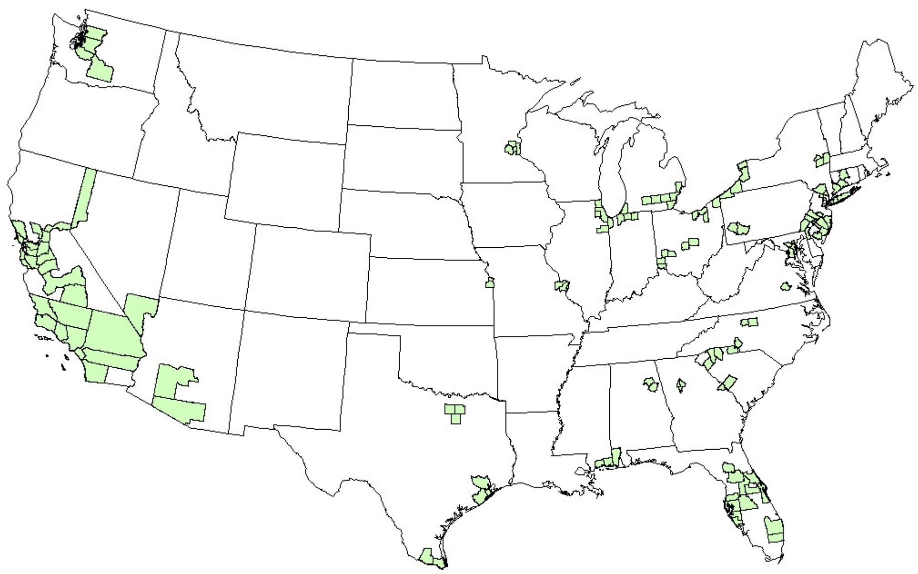


Figure A.9: 8010nw Counties



APPENDIX B

Table B.1: Description of Variable Codes

Variable Code	Description
X_i	Average County Income in Time 1 (parent income)
Y_i	Average County Income in Time 2 (dependent income)
MALE	Percent Change in the Number of Males in each county from Time 1-2
WHITE	Percent Change in the Number of Whites in each county from Time 1-2
URBAN	Percent Living in an Urban Area in each county in Time 2
EDUC	Percent with at Least a High School Degree in each county in Time 2
MIGRATE	Net County Migration Rate
occscore	Score of the Median Total Income for each Occupation in 1950 (in Hundreds of Dollars)
perwt	The Number of People in the County Population Represented by a Given Individual in the IPUMS Sample

APPENDIX C

Table C.1: Description of Regression Codes

Regression Code	Description
1040all	1910 Generation, 1940 Generation full sample
1040ff	1910 Generation maternal, 1940 Generation female
1040mf	1910 Generation paternal, 1940 Generation female
1040fm	1910 Generation maternal, 1940 Generation male
1040mm	1910 Generation paternal, 1940 Generation male
1040w	1910 Generation white, 1940 Generation white
1040nw	1910 Generation non-white, 1940 Generation non-white
8010all	1980 Generation, 2010 Generation full sample
8010ff	1980 Generation maternal, 2010 Generation female
8010mf	1980 Generation paternal, 2010 Generation female
8010fm	1980 Generation maternal, 2010 Generation male
8010mm	1980 Generation paternal, 2010 Generation male
8010w	1980 Generation white, 2010 Generation white
8010nw	1980 Generation non-white, 2010 Generation non-white

APPENDIX D

Table D.1: IGEs and Regression Diagnostics Across Spatial Model Specifications for 1910-9140 and 1980-2010 Without Controls

	Regression Coefficients					Regression Diagnostics		
Regression Code	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID	N	Moran's I, QC	Moran's I, ID
1040all	0.332***	0.264***	0.264***	0.279***	0.278***	2775	10.956***	43.776***
	(0.022)	(0.019)	(0.017)	(0.018)	(0.016)			
1040ff	0.428***	0.240***	0.257***	0.222***	0.233***	596	5.636***	20.815***
	(0.029)	(0.045)	(0.031)	(0.035)	(0.026)			
1040mf	0.546***	0.360***	0.408***	0.352***	0.398***	1219	10.642***	45.376***
	(0.052)	(0.049)	(0.045)	(0.048)	(0.044)			
1040fm	0.243***	0.180***	0.166***	0.156***	0.146***	820	7.007***	24.937***
	(0.014)	(0.018)	(0.015)	(0.017)	(0.013)			
1040mm	0.412***	0.358***	0.356***	0.367***	0.366***	2484	9.753***	38.473***
	(0.024)	(0.021)	(0.020)	(0.021)	(0.011)			
1040w	0.235***	0.206***	0.211***	0.212***	0.216***	2680	8.207***	33.179***
	(0.022)	(0.018)	(0.018)	(0.018)	-0.018			
1040nw	0.228***	0.206***	0.207***	0.207***	0.210***	554	3.672***	4.085***
	(0.065)	(0.048)	(0.045)	(0.047)	(0.046)			
8010all	0.945***	0.918***	0.778***	0.913***	0.797***	183	6.055***	14.748***
	(.118)	(0.103)	(0.096)	(0.098)	(0.088)			
8010ff	0.685***	0.592***	0.526	0.575***	0.526***	183	5.241***	9.338***
	(0.089)	(0.082)	(0.072)	(0.081)	(0.069)			
8010mf	0.524***	0.511***	0.427***	0.550***	0.489***	183	7.059***	15.205***
	(0.106)	(0.096)	(0.089)	(0.095)	(0.880)			
8010fm	0.359***	0.329***	0.291***	0.282**	0.264***	183	4.960***	10.872***
	(0.108)	(0.098)	(0.085)	(0.096)	(0.082)			
8010mm	0.743***	0.688***	0.633***	0.692***	0.645***	183	4.563***	12.28***
	(0.111)	(0.107)	(0.101)	(0.010)	(0.092)			
8010w	0.040	0.100	0.074	0.033	0.044	183	5.837***	13.880***
	(0.112)	(0.112)	(0.118)	(0.115)	(0.115)			
8010nw	0.166	0.138	0.151	0.080	0.112	150	1.215	2.978**
	(0.127)	(0.119)	(0.117)	(0.121)	(0.117)			

See Appendix C for regression code descriptions; ***, **, and * indicate significance at 1, 5, and 10% level respectively; All IGEs are jointly significant at the 1% level; QC/ID mean a queen contiguity/inverse distance spatial weight matrix was used respectively

APPENDIX E[9]

Table E.1: 1040all Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1910 Avg. County Income	0.160***	0.117***	0.118***	0.128***	0.121***
	(0.025)	(0.019)	(0.018)	(0.019)	(0.018)
URBAN	0.245***	0.239***	0.236***	0.230***	0.238***
	(0.019)	(0.019)	(0.018)	(0.019)	(0.018)
MIGRATE	0.154***	0.136***	0.129***	0.136***	0.144***
	(0.034)	(0.028)	(0.025)	(0.026)	(0.025)
EDUC	0.472***	0.494***	0.395***	0.496***	0.387***
	(0.074)	(0.061)	(0.055)	(0.061)	(0.055)
MALE	-0.582	-0.065**	-0.063**	-0.078***	-0.071**
	(0.041)	(0.030)	(0.030)	(0.030)	(0.030)
WHITE	0.061	0.103***	0.093***	0.085**	0.090***
	(0.038)	(0.034)	(0.034)	(0.034)	(0.034)
Constant	2.388***	2.511***	1.763***	2.360***	-0.430***
	(0.067)	(0.054)	(0.075)	(0.239)	(0.071)
N	2775	2775	2775	2775	2775
Moran's I	---	10.244***	10.244***	39.165***	39.165***
F statistic	171.58***	---	---	---	---

[9] See Appendix C for regression code descriptions; ***, **, and * indicate significance at 1, 5, and 10% level respectively; QC/ID mean a queen contiguity/inverse distance spatial weight matrix was used respectively

Table E.2: 1040ff Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1910 Avg. County Income	0.228***	0.143***	0.125***	0.122***	0.100***
	(0.037)	(0.039)	(0.035)	(0.037)	(0.033)
URBAN	0.124**	0.108*	0.114***	0.104*	0.110*
	(0.058)	(0.059)	(0.035)	(0.059)	(0.057)
MIGRATE	-0.146	-0.146	-0.080	-0.040	-0.006
	(0.149)	(0.129)	(0.120)	(0.127)	(0.120)
EDUC	1.507***	1.461***	1.112***	1.121***	0.952***
	(0.247)	(0.249)	(0.229)	(0.246)	(0.224)
MALE	0.041	0.016	0.017	0.004	0.003
	(0.190)	(0.157)	(0.151)	(0.155)	(0.150)
WHITE	-0.295*	-0.273**	-0.219**	-0.212**	-0.182*
	(0.179)	(0.113)	(0.110)	(0.114)	(0.109)
Constant	2.013***	2.237***	1.416***	2.421***	-0.345***
	(0.085)	(0.093)	(0.098)	(0.472)	(0.101)
N	596	596	596	596	596
Moran's I	---	5.635***	5.635***	15.502***	15.502***
F statistic	45.63***	---	---	---	---

Table E.3: 1040mf Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1910 Avg. County Income	0.331***	0.242***	0.260***	0.240***	0.249***
	(0.060)	(0.058)	(0.056)	(0.058)	(0.056)
URBAN	-0.044	-0.045	-0.033	-0.029	-0.025
	(0.045)	(0.049)	(0.048)	(0.049)	(0.048)
MIGRATE	-0.088	-0.048	-0.051	-0.054	-0.047
	(0.056)	(0.063)	(0.059)	(0.061)	(0.059)
EDUC	1.565***	1.434***	1.234***	1.161***	1.088***
	(0.169)	(0.175)	(0.159)	(0.177)	(0.157)
MALE	-0.152	-0.073	-0.093	-0.140	-0.144
	(0.107)	(0.095)	(0.095)	(0.097)	(0.095)
WHITE	-0.202*	-0.031	-0.053	-0.056	-0.064
	(0.114)	(0.089)	(0.086)	(0.088)	(0.085)
Constant	1.640***	1.926***	1.070***	1.959***	-0.864***
	(0.174)	(0.166)	(0.168)	(0.525)	(0.166)
N	1219	1219	1219	1219	1219
Moran's I	---	8.852***	8.852***	29.078***	29.078***
F statistic	33.83***	---	---	---	---

Table E.4: 1040fm Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1910 Avg. County Income	0.091***	0.064***	0.056***	0.057***	0.028**
	(0.015)	(0.014)	(0.014)	(0.015)	(0.013)
URBAN	0.341***	0.325***	0.325***	.322***	0.326***
	(0.027)	(0.023)	(0.023)	(0.024)	(0.023)
MIGRATE	0.145***	0.191***	0.178***	0.179***	0.207***
	(0.055)	(0.053)	(0.050)	(0.052)	(0.049)
EDUC	0.727***	0.764***	0.553***	0.666***	0.477***
	(0.117)	(0.096)	(0.093)	(0.097)	(0.090)
MALE	-0.176***	-0.126**	-0.154***	-0.190***	-0.196***
	(0.075)	(0.059)	(0.060)	(0.060)	(0.059)
WHITE	0.108	0.171***	0.161***	0.154***	0.173***
	(0.055)	(0.043)	(0.043)	(0.044)	(0.043)
Constant	2.600***	2.661***	1.902***	2.585***	-0.162
	(0.032)	(0.033)	(0.081)	(0.233)	(0.111)
N	820	820	820	820	820
Moran's I	---	8.762***	8.762***	26.219***	26.219***
F statistic	195.04***	---	---	---	---

Table E.5: 1040mm Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1910 Avg. County Income	0.161***	0.138***	0.137***	0.143***	0.135***
	(0.027)	(0.022)	(0.022)	(0.022)	(0.021)
URBAN	0.330***	0.315***	0.316***	0.308***	0.316***
	(0.022)	(0.020)	(0.020)	(0.020)	(0.020)
MIGRATE	0.199***	0.205***	0.184***	0.181***	0.186***
	(0.037)	(0.029)	(0.027)	(0.028)	(0.027)
EDUC	0.388***	0.426***	0.325***	0.448***	0.321***
	(0.072)	(0.064)	(0.058)	(0.065)	(0.058)
MALE	-0.031	-0.040	-0.035	-0.057	-0.047
	(0.042)	(0.035)	(0.035)	(0.035)	(0.035)
WHITE	0.098**	0.126***	0.122***	0.113***	0.126***
	(0.038)	(0.038)	(0.037)	(0.037)	(0.037)
Constant	2.385***	2.450***	1.827***	2.343***	-0.464***
	(0.077)	(0.063)	(0.087)	(0.190)	(0.099)
N	2484	2484	2484	2484	2484
Moran's I	---	8.826***	8.826***	31.872***	31.872***
F statistic	223.60***	---	---	---	---

Table E.6: 1040w Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1910 Avg. County Income	0.058	0.046	0.047	0.047	0.047
	(0.024)	(0.019)	(0.019)	(0.019)	(0.019)
URBAN	0.307***	0.297***	0.295***	0.284***	0.289***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)
MIGRATE	0.193***	0.185***	0.174***	0.163***	0.171***
	(0.037)	(0.029)	(0.027)	(0.028)	(0.027)
EDUC	0.232***	0.286***	0.223***	0.369***	0.249***
	(0.072)	(0.063)	(0.058)	(0.065)	(0.057)
MALE	-0.037	-0.045	-0.042	-0.053	-0.049
	(0.043)	(0.033)	(0.033)	(0.033)	(0.032)
WHITE	0.095**	0.101**	0.102***	0.090**	0.106***
	(0.044)	(0.040)	(0.039)	(0.040)	(0.039)
Constant	2.749***	2.781***	2.280***	2.695***	-0.154
	(0.068)	(0.055)	(0.089)	(0.162)	(0.117)
N	2680	2680	2680	2680	2680
Moran's I	---	6.566***	6.566***	26.343***	26.343***
F statistic	131.21***	---	---	---	---

Table E.7: 1040nw Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1910 Avg. County Income	0.185***	0.165***	0.167***	0.166***	0.166***
	(0.068)	(0.050)	(0.048)	(0.050)	(0.049)
URBAN	0.076	0.101*	0.085	0.095*	0.091*
	(0.052)	(0.054)	(0.053)	(0.054)	(0.053)
MIGRATE	0.066	0.038	0.051	0.056	0.061
	(0.058)	(0.065)	(0.063)	(0.064)	(0.063)
EDUC	0.354	0.278	0.284	0.276	0.268
	(0.265)	(0.227)	(0.221)	(0.230)	(0.224)
MALE	0.059	0.042	0.052	0.036	0.042
	(0.119)	(0.100)	(0.101)	(0.102)	(0.102)
WHITE	-0.184**	-0.173***	-0.170***	-0.173***	-0.174***
	(0.077)	(0.060)	(0.060)	(0.061)	(0.060)
Constant	2.098***	2.154***	1.707***	2.151***	0.360
	(0.166)	(0.125)	(0.164)	(0.129)	0.616
N	554	554	554	554	554
Moran's I	---	3.294***	3.294***	3.326***	3.326***
F statistic	7.02***	---	---	---	---

Table E.8: 8010all Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1980 Avg. County Income	0.624***	0.621***	0.517***	0.649***	0.558***
	(0.128)	(0.126)	(0.110)	(0.119)	(0.100)
URBAN	0.517***	0.344**	0.408***	0.370***	0.398***
	(0.123)	(0.118)	(0.109)	(0.110)	(0.100)
MIGRATE	-0.046	0.198	0.068	0.289*	0.178
	(0.192)	(0.179)	(0.158)	(0.170)	(0.147)
EDUC	0.986***	1.10***	0.918***	0.966***	0.923***
	(0.282)	(0.270)	(0.235)	(0.250)	(0.219)
MALE	0.494	0.159	0.338	0.219	0.251
	(0.482)	(0.473)	(0.479)	(0.450)	(0.446)
WHITE	-0.200	-0.143	-0.191	-0.056	-0.092
	(0.145)	(0.123)	(0.119)	(0.118)	(0.111)
Constant	2.950**	3.065**	1.177	2.667**	-5.981***
	(1.266)	(1.203)	(1.086)	(1.156)	(1.160)
N	183	183	183	183	183
Moran's I	---	4.897***	4.897***	12.527***	12.527***
F statistic	18.96***	---	---	---	---

Table E.9: 8010ff Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1980 Avg. County Income	0.497***	0.478***	0.393***	0.461***	0.387***
	(0.094)	(0.084)	(0.074)	(0.082)	(0.073)
URBAN	0.297**	0.167	0.223*	0.247*	0.247**
	(0.141)	(0.129)	(0.120)	(0.126)	(0.073)
MIGRATE	-0.012	0.233	0.054	0.352*	0.118
	(0.205)	(0.187)	(0.162)	(0.189)	(0.161)
EDUC	1.355***	1.343***	1.194***	1.247***	1.243***
	(0.239)	(0.252)	(0.221)	(0.245)	(0.218)
MALE	-0.049	-0.500	-0.190	-0.444	-0.257
	(0.538)	(0.491)	(0.493)	(0.493)	(0.491)
WHITE	-0.516***	-0.493***	-0.455***	-0.446***	-0.393***
	(0.113)	(0.111)	(0.110)	(0.114)	(0.110)
Constant	4.294***	4.600***	2.368***	4.641***	-3.288***
	(0.891)	(0.762)	(0.730)	(0.761)	(1.149)
N	183	183	183	183	183
Moran's I	---	4.984***	4.984***	8.837***	8.837***
F statistic	20.50***	---	---	---	---

Table E.10: 8010mf Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1980 Avg. County Income	0.149	0.179	0.140	0.252**	0.221**
	(0.119)	(0.112)	(0.010)	(0.111)	(0.096)
URBAN	0.651***	0.443***	0.473***	0.492***	0.501***
	(0.137)	(0.129)	(0.116)	(0.125)	(0.113)
MIGRATE	-0.064	0.040	0.027	0.170	0.093
	(0.207)	(0.198)	(0.171)	(0.200)	(0.169)
EDUC	1.450***	1.411***	1.209***	1.244***	1.193***
	(0.331)	(0.293)	(0.252)	(0.283)	(0.248)
MALE	0.302	-0.362	0.052	-0.201	0.006
	(0.548)	(0.526)	(0.521)	(0.524)	(0.515)
WHITE	-0.538***	-0.405***	-0.443***	-0.292***	-0.329**
	(0.152)	(0.142)	(0.131)	(0.144)	(0.130)
Constant	7.145***	7.046***	3.907***	6.160***	-2.864**
	1.174	(1.130)	(1.087)	(1.151)	(1.225)
N	183	183	183	183	183
Moran's I	---	5.464***	5.464***	10.572***	10.572***
F statistic	14.74***	---	---	---	---

Table E.11: 8010fm Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1980 Avg. County Income	0.084	0.138	0.077	0.088	0.050
	(0.110)	(0.105)	(0.091)	(0.098)	(0.086)
URBAN	0.610***	0.437***	0.492***	0.512***	0.513***
	(0.169)	(0.163)	(0.153)	(0.150)	(0.143)
MIGRATE	-0.107	0.342	0.035	0.446**	0.169
	(0.258)	(0.247)	(0.207)	(0.224)	(0.195)
EDUC	1.488***	1.632***	1.349***	1.582***	1.413***
	(0.319)	(0.315)	(0.279)	(0.292)	(0.263)
MALE	0.136	-0.128	0.086	-0.172	-0.021
	(0.667)	(0.615)	(0.625)	(0.584)	(0.591)
WHITE	-0.410**	-0.359**	-0.359***	-0.272**	-0.287**
	(0.194)	(0.140)	(0.140)	(0.136)	(0.132)
Constant	8.355***	7.879***	5.728***	8.191***	-1.008
	(1.033)	(0.953)	(1.002)	(0.935)	(1.098)
N	183	183	183	183	183
Moran's I	---	4.225***	4.225***	10.496***	10.496***
F statistic	8.84***	---	---	---	---

Table E.12: 8010mm Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1980 Avg. County Income	0.562***	0.516***	0.484***	0.545***	0.514***
	(0.125)	(0.125)	(0.112)	(0.118)	(0.102)
URBAN	0.624***	0.490***	0.523***	0.545***	0.506***
	(0.146)	(0.143)	(0.132)	(0.118)	(0.121)
MIGRATE	(0.105)	0.146	0.018*	0.284	0.174
	(0.233)	(0.228)	(0.198)	(0.212)	(0.183)
EDUC	0.942***	1.128***	0.900***	1.048***	0.900***
	(0.359)	(0.328)	(0.287)	(0.300)	(0.266)
MALE	0.269	0.093	0.211	0.029	0.083
	(0.603)	(0.601)	(0.597)	(0.554)	(0.552)
WHITE	-0.066	-0.037	-0.071	0.096	0.034
	(0.198)	(0.160)	(0.150)	(0.152)	(0.139)
Constant	3.487***	4.015***	1.918	3.614***	-5.691***
	(1.257)	(1.261)	(1.186)	(1.200)	(1.281)
N	183	183	183	183	183
Moran's I	---	3.635***	3.635***	10.805***	10.805***
F statistic	14.45***	---	---	---	---

Table E.13: 8010w Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1980 Avg. County Income	-0.053	0.046	-0.007	-0.025	-0.018
	(0.083)	(0.095)	(0.101)	(0.095)	(0.094)
URBAN	1.006***	0.814***	0.849***	0.823***	0.840***
	(0.138)	(0.136)	(0.124)	(0.124)	(0.113)
MIGRATE	-0.230	-0.008	-0.129	0.095	-0.011
	(0.208)	(0.209)	(0.183)	(0.200)	(0.171)
EDUC	1.597***	1.756***	1.416***	1.608***	1.391***
	(0.307)	(0.282)	(0.246)	(0.258)	(0.228)
MALE	0.757	0.401	0.629	0.433	0.576
	(0.506)	(0.552)	(0.553)	(0.524)	(0.517)
WHITE	-0.180	0.033	-0.084	0.084	-0.006
	(0.223)	(0.131)	(0.124)	(0.123)	(0.115)
Constant	9.229***	8.280***	5.972***	8.909***	-0.643
	(0.957)	(1.001)	(1.241)	(1.051)	(1.240)
N	183	183	183	183	183
Moran's I	---	3.749***	3.749***	10.146***	10.146***
F statistic	18.01***	---	---	---	---

Table E.14: 8010nw Regression Results and Diagnostics Across Model Specification

Variable	Regression Coefficients				
	OLS	Spatial Error, QC	Spatial Lag, QC	Spatial Error, ID	Spatial Lag, ID
1980 Avg. County Income	0.135	0.134	0.128	0.108	0.101
	(0.125)	(0.113)	(0.113)	(0.115)	(0.114)
URBAN	0.510	0.498	0.476	0.412	0.440
	(0.411)	(0.339)	(0.329)	(0.346)	(0.326)
MIGRATE	-0.556	-0.554	-0.545	-0.609	-0.541
	(0.459)	(0.421)	(0.419)	(0.444)	(0.416)
EDUC	-1.378**	-1.372**	-1.336**	-1.303**	-1.272**
	(0.613)	(0.582)	(0.581)	(0.603)	(0.578)
MALE	2.477*	2.500*	2.510*	2.546*	2.435*
	(1.464)	(1.457)	(1.448)	(1.437)	(1.438)
WHITE	-0.265	-0.260	-0.249	-0.163	-0.174
	(0.258)	(0.283)	(0.281)	(0.299)	(0.285)
Constant	9.242***	9.259***	8.845***	9.565***	6.043**
	(1.421)	(1.235)	(1.379)	(1.265)	(2.554)
N	150	150	150	150	150
Moran's I	---	0.320	0.320	1.666*	1.666*
F statistic	3.81***	---	---	---	---