The Impact of Suburbanization on Poverty Concentration: Using Transportation Networks to Predict the Spatial Distribution of Poverty

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Abstract

The purpose of this paper is to investigate the determinants of concentrated poverty, a phenomenon where socioeconomically deprived groups are heavily concentrated in particular neighborhoods in a metropolitan area. Drawing on Land Use Theory and the Spatial Mismatch Hypothesis, I develop a theory that identifies suburbanization as a principal cause of poverty concentration. Using interstate highway expansion as a source of exogenous variation in suburbanization rates, I evaluate this relationship in 240 U.S. Metropolitan Statistical Areas (MSAs) from 1960-1990, with concentrated poverty measured at the tract level. Panel regressions with MSA Fixed Effects find a positive and significant relationship between highway expansion and increased poverty concentration under a variety of specifications, including alternative measures of highways and an instrumented measure of urban population decline.

JEL Codes: I30; J61; R13; R40

Keywords: Poverty Concentration; Suburbanization; Highways; Transportation Networks; Spatial Mismatch

I. Introduction

Since the end of World War II, metropolitan areas in the United States have experienced tremendous geographic sprawl, with the growth of suburban areas far outpacing the growth of the central cities they surround. These developments in socioeconomic spatial arrangements have consequences for both the rich and the poor, as the demographic composition of individual neighborhoods *and* of the larger metropolitan area affect how economic opportunities are shared and what social outcomes are achieved. While much attention has been paid in previous research to the dynamics of race and class segregation and the neighborhood effects they produce, in this paper I focus attention particularly on how the poor and their communities are affected by this process of suburbanization. Specifically, the phenomenon of poverty concentration—the existence of neighborhoods with high to extreme poverty rates among their population—has important implications that make it worthy of analysis, as such a heavy concentration of poor and low-skilled persons can cause serious deleterious effects for the residents of those neighborhoods and surrounding neighborhoods, whether rich or poor.

If suburbanization in fact implies a level of residential segregation that creates more homogenous demographics within communities, as many previous scholarly reports have indicated (Tiebout 1956; Squires and Kubrin 2004; Howell-Moroney 2005; Joassart-Marcelli, Musso and Wolch 2005), then it is possible that suburbanization in turn has increased the incidence of poverty concentration by creating a dynamic of geographic distancing that causes the poor to coalesce involuntarily in neighborhoods with undesirable features, features that should reasonably raise concerns for policymakers. These features include: 1) social interactive effects, such as lack of social cohesion and poor collective efficacy; 2) geographic effects, such as poor access to public services; and 3) institutional effects, such as neighborhood stigmatization and poor local institutions (Joassart-Marcelli et al 2005). And given these conditions, if suburbanization is indeed having a causal effect that is increasing poverty concentration, then this may consequently lead to *even more* suburbanization and urban sprawl as those who can afford to leave impoverished neighborhoods (i.e., the affluent) move away from those neighborhoods, which are historically close to the central city.

In this paper, I explore the mechanisms through which increased suburbanization relates to higher amounts of poverty concentration in terms of the number of communities affected within a metropolitan area. The three related mechanisms I explore are: 1) the movement of employment opportunities toward suburban areas and the high-skilled labor that locates there; 2) the Spatial Mismatch model, a factor analysis that focuses on skill complementarity and the inability of poor residents to locate closer to low-skilled job opportunities; and 3) the persistence of poverty due to heavy resource demands and limited resource supply in extreme-poverty neighborhoods, resulting to poor local economic development and educational outcomes. In order to investigate the impact of these suburbanization-induced phenomena on poverty concentration, I examine theoretically how the exogenous variation in suburbanization caused by the expansion of federal interstate highways has likely affected the spatial arrangement of poverty in Metropolitan areas. Finally, I will undertake an econometric panel analysis to determine if the relationship between suburbanization and poverty concentration exists and the significance of that relationship.

II. Literature Review

Residential and socioeconomic segregation have been topics of frequent inquiry in the fields of demographic and urban studies, as these trends have important political and economic implications. Massey (1996) undertook a massive study of the historical trends of geographic class segregation and social mobility, illuminating how the industrial revolution and its new transportation technologies enacted a trend of isolationist spatial arrangements that would not reverse until World War II, when a swelling and dominant middle class began dampening socioeconomic inequality and creating more mixed residential communities. However, "after 1970…the promise of mass social mobility evaporated and inequality returned with a vengeance, ushering in a new era in which the privileges of the rich and the disadvantages of the poor were compounded increasingly through geographic means" (ibid pg. 395). The postindustrial economy instituted an "hourglass" economic structure with high-paying jobs for the wealthy, educated class, few jobs for the decently educated middle class, and many low-paying, low-skilled jobs. The result was a drastic drop in social and residential mobility for the lower classes. Throughout this history, the poor urbanized to a large extent (75% in 1990), and that trend has not reversed, while affluent populations lived in neighborhoods that had, on average, at least 50% affluent residents, indicating the extent of residential stratification.

Howell-Moroney (2005) and Li, Campbell, and Fernandez (2013) further the analysis of mobility limitations and connect it with the Spatial Mismatch Hypothesis (SMH), although they focus primarily on poor minority groups. The SMH states that low- and high-skilled labor are significantly complementary and require socio-geographic proximity to each-other to be best utilized, and job locations typically move toward the rich, especially in the case of services. Accordingly, the SMH also proposes that residential segregation reduces employment opportunities for the poor—and particularly poor minorities—due to "the physical distance between residence and potential jobs and the limited access to networks informing people about job opportunities" (2645).

The results of the Howell-Moroney (2005) study showed that, for minorities, residential segregation and its neighborhood effects—underfunded or poorly performing public schools, etc.—do have a significant impact on youths' educational attainment. In turn, his results indicate that unemployment probability for adults is a function of educational attainment and the extent of Spatial Mismatch. This seems to indicate that suburbanization—which implies a degree of class/race segregation, as poor individuals lack mobility—both decreases educational attainment and decreases employment prospects, which likely will lead to higher poverty rates in the present and future for affected communities.

Li et al (2013) achieve similar results, demonstrating that higher racial or skill segregation resulted in lower economic growth by way of the causal impact of limited skill-based integration between high-skilled and low-skilled workers; they therefore recommended more proactive policies to promote socioeconomic mobility. Blackley (1990) undertakes a similar analysis to determine the impact of Spatial Mismatch on 10 low-skilled occupations in a given metropolitan area. Their analysis only yielded a significant effect on unemployment rates for females living in central cities, as these women had trouble obtaining employment at low-skill suburban job opportunities. He identified high school graduations rates as a more significant variable in determining unemployment, which has implications for this paper in analyzing the relationship between suburbanization and sub-par education spending in poor neighborhoods due to public fiscal restrictions.

Baum-Snow (2007) and Li et al (2013) show that residential stratification is caused largely by market processes, but also that they are influenced by legal and political developments. These results have additional implications for the mobility of poor residents of metropolitan areas. For instance, American citizens prefer to locate in more homogenous neighborhoods that share their demographic profile, particularly in terms of income/status, ethnicity, culture, and values (Baum-Snow 2007). As a result, homebuilders are given incentives to create large communities composed exclusively of homes of similar size and price, thus maintaining class divisions and denying poor residents housing opportunities nearby. These middle- and upper-class communities also sometimes establish independent municipalities, school systems, or jurisdictions, which allows them to institute local building and zoning codes that help discriminate against particular types of residents, such as renters (Li et al 2013). These mechanisms are part of the pattern of suburbanization, and they in turn increase the likelihood of poverty concentration through limitations on mobility.

Additionally, Massey (1990) and Stoll, Holzer, and Ihlanfelt (2000) explore the disproportionate employment growth of suburbs compared to their central cities, particularly with regard to low-skilled employment opportunities. As the migration of high-skilled labor and advancement of communication technologies have motivated more businesses and employers to locate in suburban areas, a friction has developed as poor, low-skilled workers are unable to relocate closer or access adequate (public) transportation to those opportunities. Therefore, if suburbanization continues to increase the displacement of employment opportunities to the suburbs, it is reasonable to expect increased unemployment and its associated socioeconomic ills in central cities, increasing the incidence of poverty concentration.

Lastly, Baum-Snow (2007) examined the influence of federal and state-funded highways on suburbanization in metropolitan areas, showing that the number of highways emanating from or running through the central city of an MSA caused significant reductions in the population of that central city, holding overall metropolitan population constant. Due to the exogenous nature of the highway projects initiated by the federal government in 1947, Baum-Snow's study provides a valuable instrumental variable for the analysis undertaken in this paper, as variable highway construction across the United States can be used to investigate the impact of spatial metropolitan expansion—or "suburbanization"— on poverty concentration.

III. Theoretical Framework

The empirical analysis undertaken in this paper is based on a theoretical framework that draws on two previous theories—Land Use Theory and the Spatial Mismatch Hypothesis—and on the well-documented notion of immobility among socioeconomically disadvantaged residents. Through these concepts, the framework is constructed to represent the relationship between expanded transportation networks (i.e., highways) and poverty concentration through the process of suburbanization.

1. History of the Federal Highway System

Before exploring the theoretical mechanisms through which we expect suburbanization to affect the concentration of poverty, it is necessary to review the nature of 20th Century highway expansion and its role as a source of exogenous variation in transportation network development. Initiated by the Federal Aid Highway Act of 1944 and finally brought to fruition by the 1956 Interstate Highway Act, the U.S. interstate highway system was explicitly motivated by national interests rather than regional or local ones. While tailoring recommendations at the tail end of World War II, the National Interregional Highway Committee's primary considerations were the War Department's proposed highway network, agricultural production, industrial hubs, and national population distributions (Baum-Snow 2007). Additionally, 90 percent of this new network was to be *federally* funded, and only 341 miles of the 41,000-mile network proposed by the 1956 Interstate Highway Act already existed (ibid). Therefore, while there was likely some variation among MSAs in their lobbying for highways and for first-priority construction, we have strong reasons to believe that federal highway expansion in a specific MSA is for the most part not endogenous to local conditions.

2. Land Use Theory

Developed extensively by Alonso (1964) and Mills (1967), Land Use Theory proposes a mechanism through which increased transportation infrastructure causes suburbanization. The basic form of the theory assumes that all economic activity occurs in a centralized location (say, a central city business district) and that rental/land prices are a function of their time-distance from that location. Accordingly, the exogenous introduction of a highway that connects the central city to surrounding suburban areas lowers the average commuting time from those areas, thus effectively lowering the cost of commuting and increasing the supply of land accessible to the central city. This leads the equilibrium rental rate to fall across the metropolitan area, which reduces the population density through a price effect. Moreover, lower commuting costs raises net incomes all else equal, and since space is a normal good, the associated income effect will further reduce population density as people move into the suburbs. The effect, then, of a new highway system is suburbanization.

3. Spatial Mismatch Hypothesis

The Spatial Mismatch Hypothesis (SMH) is the idea that economic restructuring and residential spatial distributions have caused employment opportunities for low-skilled workers to be located far away from their residences. Due to the commuting costs and information-gathering costs and difficulties associated with increased distances from employers, the implication of the hypothesis is that lower-skilled persons or persons of lower socioeconomic status have increased difficulty finding gainful employment as employment suburbanizes. Given that employment opportunities are increasingly located outside central cities due to the process of suburbanization, this hypothesis indicates that suburbanization may lead to higher rates of unemployment among low-skilled persons due to metropolitan sprawl, and this in turn may lead to higher rates of poverty concentration.

4. The Theoretical Model

Using these theories, it can be expected that highways will affect the spatial distribution of residents in such a way as to increase suburbanization and, correspondingly, increase the prevalence of poverty concentration. Drawing on the micro-level analysis of individual preferences for housing and consumption under the Land Use Theory, new transportation networks that effectively increase the supply of land for residential and commercial use will lead to population decentralization away from the central city. Given the differential opportunities available to different socioeconomic classes (such as savings and having a car), this decentralization—or "suburbanization"—will cause significant residential segregation of those classes, leading to increased poverty concentration. Moreover, the decrease in population density across a Metropolitan Statistical Area (MSA) has been shown to cause employment decentralization as well; these joint processes of residential and employment decentralization, in accordance with the Spatial Mismatch Hypothesis, will cause increased unemployment among neighborhoods comprised of low-skilled workers (i.e., the lower socioeconomic classes). This will lead to further increases in poverty concentration, all else equal.

This theoretical model is empirically studied using a fixed effects panel regression with groupings of MSA observations, allowing for an analysis of the relationship between changes in poverty concentration rates in an MSA and the change in the level of highway network development in that same MSA, while holding constant unobserved heterogeneity across MSAs.

The relationship is estimated using the following equations:

(1) $$\Delta PovertyConc_{i(t+1)} = \beta_0 + \beta_1(\Delta Highways_{it}) + \beta_2\Delta \log N_{it} + \beta_3 \Delta POV_{i(t+1)} + \beta_4 \Delta G_{it} \quad + \beta_5 \Delta \% Black_{it} + \varepsilon_i + \ \varepsilon_{it}$$

and

First Stage Instrumental Variable Regression:

(2a)

$$\Delta\, log(CC\ Pop_i) = \beta_0 + \beta_1(\Delta Highways_i) + \beta_2 \Delta median\ income_i + \ \mu_i$$

Second Stage:

(2b) $$\Delta PovertyConc_i = \beta_0 + \beta_1 \Delta log(CC\ Pop_i) + \beta_2 \Delta \log N_i + \beta_3 \Delta POV_i + \beta_4 \Delta G_i + \beta_5 \Delta \% Black_i + \varepsilon_i$$

note: Change, or Δ, will be between the decennial census dates

Looking at Metropolitan Statistical Areas (MSAs) in 1960, 1970, 1980, and 1990, "Δ" denotes change in each decennial period. $PovertyConc_i$ represents the proportion of census tracts with a poverty rate above a certain threshold (20%, 30%, 40%) in MSA *i*. The primary explanatory variable, $Highways_i$, is operationalized using a variety of measures of highway expansion across the models; these measures include the number of highway "rays" that emanate from a central city into the surrounding area in MSA *i*, and—alternatively—the total mileage of those "rays" that has been completed at each period in time. N_i represents the total population of MSA i, controlling for the impact of population growth on poverty concentration. POV represents the overall poverty rate of MSA i, which controls for changes in prevalence of poverty across the entire metropolitan area. $Median\ Income_i$ represents the median family income for MSA *I* in a given period. Lastly, G_i is an indexed Gini coefficient to control for differences in income distribution across MSAs, as such distributive disparities may affect relative demand for different types of housing (i.e., suburban developments). This coefficient is calculated using the methodology from Baum-Snow (2007), where the concentration of each industry in the MSA is weighted compared to the national average and combined with the prevailing national wage rate for that industry. The purpose of the Gini coefficient is to control for the effect that variable income distribution may have on relative demand for different types of housing.

IV. Data/Methodology

Most of the data and calculations referred to below have been compiled by Professor Nathaniel Baum-Snow of Brown University. Information that has not been compiled in Baum-Snow's data set is from Brown University's Longitudinal Tract Data Base (LTDB).

"Primary" Metropolitan Statistical Areas (Unit of Analysis) & Population Data

The *County and City Data Books* (CCDB) contain decennial census data aggregated to the county level and the city level for cities with at least 25,000 inhabitants. Metropolitan Statistical Areas (MSAs) are constructed by aggregating the counties according to groupings in 2000. Only MSAs that have at least 30,000 total citizens and that have a central city of at least 25,000 are included in this analysis. If an MSA meets the overall population criterion but not the central city population criterion, then it is combined with the nearest MSA that has a central city. Special MSA definitions have been assigned for "megapolitan" areas in the New England area (called NECMAs), and these areas are kept aggregated in my data. Each MSA is assigned a single central city, using the census-defined central city with the largest population in 1950; the boundaries of these central cities are kept constant at their current boundaries in order to be consistent with the LTDB data.

Central Business Districts (CBDs)

Central Business Districts are taken from the 1982 *Economic Censuses' Geographic Reference Book*, which defines this district by agglomerating all census tracts considered to be in the district by local businesspeople.

Interstate Highway Rays & Non-Interstate Highways

Rays are defined as interstate and non-interstate highways that pass within one mile of the central business district in the central city of an MSA (defined above) and connect to an area outside the 1950-defined central city, based on Baum-Snow's (2007) examinations of maps in the 2004 version of *Road Atlas*. Information on the construction and completion of the identified highways is drawn from the Federal Highway Administration's (FHA) *Form PR-511 Database*, which lists segment lengths, funding sources, and the dates at which different portions of the highway were completed. Since the database only has information on half of locally funded segments of highway construction, Baum-Snow used the "Route Log and Finder List" published by the FHA to fill in the missing data.

The PR-511 data are then used to allocate the number of miles of a particular highway in each county of an MSA for a given year. Those county mileages are then aggregated to form the mileage present for each "ray" in an MSA in each year. As in Baum-Snow (2007), I consider a "ray" to be operational when at least one mile is completed and open at the beginning of the year.

MSA Poverty Rates & Poverty Concentration Measures

Poverty rates for MSAs from 1960-1990 are constructed by using a weighted average of the counties of a given MSA for each period, using data drawn from the Brown University's Longitudinal Tract Data Base (LTDB). To create these composite poverty rates, each county's poverty rate is weighted by its proportion of the MSA's total population. In this data set, poverty is defined as an individual living below the federal poverty threshold, which is recalculated and published decennially by the Census Bureau.

Additionally, the LTDB database applies constant 2010 tract and county geography to all previous decennial census periods, allowing for some amount of comparability of tracts ("neighborhoods") across periods (1970 to 2000). Poverty rates for census tracts are constructed using sample-based data due to limitations in the longitudinal availability of U.S. Census poverty measures.

Using these data, I measure poverty concentration as the proportion of census tracts within an MSA that have a poverty rate above a certain threshold, where $PovConc = \frac{(\#\ of\ tracts\ above\ threshold)}{\#\ of\ total\ tracts\ in\ MSA}$. Along with the poverty rate variable, these poverty concentration variables are assumed to respond with a one period (i.e., decade) lag to account for the fact that social and economic responses to highway expansion are likely to be gradual. Therefore, MSA observations in the year 1960 are associated with a poverty concentration measurement in 1970, and so on. Additionally, I multiply the poverty concentration variables and the MSA poverty rate variable by 100 in the regression analysis to so that the term represents percentages rather than fractions.

Income Distribution Measure

The PUMS data (starting in 1960) provide the information necessary to construct Gini coefficients specific to each MSA, which will control for the endogenous effect of income distribution on suburbanization rates. The employment shares across ten one-digit coded industries are held constant for each MSA based on 1940 calculations. Then, using PUMS data on the evolution of national skill prices for individuals working in those industries (excluding data from the state in which the MSA is located), the change in the Gini coefficient for each time period is estimated based on relative wage movements.

Summary Statistics

(Number of MSAs in data=240; Average # of Observations per MSA = 3.9)

Variable	1950*	1960	1970	1980	1990	Min	Max
Proportion of Tracts w/ Poverty Concentration ≥40%	X	.027 (.066)	.025 (.04)	.052 (.065)	.039 (.048)	0	.55
Proportion of Tracts w/ Poverty Concentration ≥30%	X	.064 (.101)	.064 (.073)	.105 (.094)	.092 (.080)	0	.78
Proportion of Tracts w/ Poverty Concentration ≥20%	.146 (.148)	.162 (.168)	.149 (.108)	.207 (.127)	.197 (.120)	0	.86
Total Rays through CC in MSA	.0625 (.34)	1.27 (1.56)	2.81 (2.19)	3.17 (2.25)	3.35 (2.32)	0	15
Poverty Rate	X	.129 (.057)	.119 (.040)	.132 (.047)	.121 (.040)	.044	.456
Simulated Gini Coefficient	.34 (.033)	.36 (.026)	.36 (.020)	.35 (.015)	.37 (.012)	.31	.40
Black % of Population	X	9.70 (10.88)	9.52 (9.76)	10.29 (10.17)	10.81 (10.33)	0	45.77
Log Population	12.2 (1.04)	12.4 (1.05)	12.6 (1.07)	12.7 (1.06)	12.8 (1.09)	10.43	16.65
Miles of Highway Rays Completed	0.28 (.141)	7.28 (.938)	33.75 (2.97)	42.92 (3.65)	45.42 (3.81)	0	295
Log Central City Population	11.37 (1.04)	11.55 (1.01)	11.66 (1.00)	11.67 (0.98)	11.70 (1.00)	10.14	15.88
Median Family Income	22718 (3466)	31925 (4677)	40849 (5311)	33137 (5015)	32432 (5534)	11109	62079

*: Xs denote missing values due to data unavailability

Procedure & Expectations

My objective is to analyze the relationship between the number of highways emanating from or running through the central city of a MSA—a source of exogenous variation in suburbanization rates—and the prevalence of poverty concentration. I consider data on census tracts from 1960-1990 collected by the United States Census Bureau, operating under the assumption that census tracts are a representative proxy for "neighborhoods", the geographic and socioeconomic unit where concentrated poverty is theorized to be operative. Because my unit of analysis in the panel regression is the "metropolitan area", I focus only on census tracts located within small and large metropolitan areas (determined by the Office of Management and Budget's published Metro Statistical Areas). For each metropolitan area, I sort the tracts based on their poverty rate and subsequently code each tract depending on whether they fall into categories of low (<20%) poverty rate, moderate poverty rate (20%+), high poverty rate (30%+), or extreme poverty rate (40%+).

After collecting data on the 240 U.S. metropolitan areas, I determine the relationship between suburbanization and poverty concentration by running a series of panel regressions including Fixed Effects, Random Effects, and Two-Stage Least Squared (instrumental variables). In each model, I proxy for suburbanization using a measure highway expansion, including: **1) the # of highways emanating from the central city within 1 mile of the Central Business District (CBD); 2) the # of highways emanating from the central city within 4 miles of the CBD**; and **3) the # of miles constituting those highways.** For the two-stage least squared (2SLS) panel regressions, I instrument for central city population using 1-mile definition highway rays and median family income. Additionally, I also include a long-difference 2SLS model that uses *overall* changes from 1960 to 1990 for each variable. Each of these models is replicated for three different poverty concentration thresholds—40%+, 30%+, and 20%+.

My expectations are that levels of highway system development—and, thus, levels of suburbanization— will be positively related to the three measures of poverty concentration indicated above. Intuitively, I expect the relationship between suburbanization and poverty concentration to appear less robustly positive at the 20%+ level than at either the 30%+ or 40%+ levels of poverty concentration, as this more moderate measure of concentration is likely to capture and respond to a much larger catalog of causes than can be incorporated in my model. I theorize that the various measures of highway expansion used in the following regressions will be statistically significant more frequently and more robustly in the 40%+ threshold models than using any other threshold, as suburbanization's influence on *extreme* poverty concentration is less likely to be confounded by the numerous other determinants of moderate concentrated poverty.

I also expect poverty concentration to be more pronounced in the MSAs of the Northeast and Midwest regions than in the South or West regions, as the former U.S. regions had already experienced a much greater degree of urbanization and industrialization prior to the introduction of federal highways, and therefore they are inherently more likely to suffer a larger number of densely populated urban communities with high levels of the unemployed and the working-class poor.

V. Results & Discussion

To validate the choice to use fixed effects in these panel regressions, it was necessary to begin by running a Hausman test. This test determines the applicability of Fixed Effects (FE) assumptions to a particular model by checking that omitted individual characteristics of each observational entity (i.e., MSA) are not correlated with the individual characteristics of any other independent variable in the sample.

The results of the Hausman test (see figure 1, appendix) indicate that a Fixed Effects panel regression is indeed appropriate for this model. However, one drawback of Fixed Effects regressions is that they are unable to capture the effects of time-invariant MSA characteristics; for this reason, I employ Random Effects regressions later in the section to analyze the impact of time-invariant MSA features such as geographic region and proximity to borders or coasts.

1. Primary Panel Regressions

Table 1 below displays the results of panel regressions using MSA fixed effects under multiple specifications. In models (1)-(3), the primary explanatory variable is the number of rays running within 1 mile of the central city's CBD. All three models account for a significant proportion of the variation in poverty concentration, with the lowest adjusted R^2 equal to .255 and highest equal to .523. Moreover, change in highway development is a statistically significant ($p< .001$) determinant of change in poverty concentration in the models using the 40%+ or 30%+ thresholds. In Model (1), the coefficient on highway rays is 0.480. By multiplying this coefficient by the standard deviation of highway rays, it is possible to examine the "economic effect" of highway change in this model, as standardizing coefficients by the variable's degree of variation allows us to make comparisons across the coefficients of multiple variables. After a one standard deviation increase in the number of MSA highway rays, the model predicts an increase of 0.71 points in the percentage of MSA tracts with poverty concentration above

40% (for example, from 3.0% to 3.71%). Model (2) uses a lower threshold (30%+), but the coefficient on highways has a very similar magnitude (0.654) and remains significant at the .001 level. As expected, highways are not a statistically significant predictor of poverty concentration when employing the 20%+ threshold (Model 3), as tracts with 20%+ poverty are likely influenced by a much larger number of factors.

While highway rays—the mechanism employed here to operationalize the trend of suburbanization—clearly have a significant impact on poverty concentration rates, several of the controls included in the sample also prove to be statistically significant, and in some cases they display a more powerful effect on spatial poverty distribution than rays. Not surprisingly, the overall MSA poverty rate exerts a strong and statistically significant influence on the level of poverty concentration. In the extreme-poverty model (40%+), the coefficient on MSA poverty rate is 1.027, and therefore a one standard deviation increase in poverty rate (4.73) would result in a 4.86-point increase in the percentage of tracts with poverty concentration. In the high-poverty and moderate-poverty models, the coefficients were significantly higher (1.63 and 2.79, respectively). The fact that these coefficients are all above one indicates that for a one percent increase in the poverty rate, we can we can expect a more than one percent increase in the rate of poverty concentration. Given that the theoretical work presented earlier indicates that suburbanization entails residential segregation, it is no surprise that increases in poverty are concentrated rather than spread evenly among an MSA's communities. This introduces an interesting potential mechanism of spatial poverty distribution, as these high coefficients indicate that poverty tends to consolidate in particular areas (i.e., tracts), and this possibility should be explored further.

Table I

Panel Regressions with Fixed Effects, 1960-1990: Determinants of Poverty Concentration Growth in Metropolitan Statistical Areas (MSAs)

Coefficients represent change in % of Tracts with a Poverty Rate above a certain threshold (40%+, 30%+, or 20%+) in an MSA	(1) 40%+	(2) 30%+	(3) 20%+
Central City Interstate Rays, 1-mile definition	0.480*** [0.138]	0.654*** [0.169]	0.459 [0.257]
Natural Log of Population	3.836*** [0.480]	5.455*** [0.585]	6.907*** [0.891]
MSA Poverty Rate (%)	1.027*** [0.0478]	1.625*** [0.0583]	2.790*** [0.0888]
Simulated Gini Coefficient	-15.17 [9.755]	41.30*** [11.90]	123.5*** [18.10]
Black % of Population	0.0238 [0.0582]	0.0857 [0.0710]	0.308** [0.108]
Constant	-53.27*** [6.648]	-97.91*** [8.108]	-152.7*** [12.34]
No. of Observations Adjusted R-squared	932 0.255	932 0.442	932 0.523

Standard Errors in Brackets
* p<0.05 ** p<0.01 *** p<0.001

Additionally, the simulated Gini coefficient created by Baum-Snow (2007) turns out to be statistically significant at the 99.9% confidence level and to exert a strong influence in models 1 and 2, but not in model 3. Using 20%+ and 30%+ concentration thresholds, the coefficient estimates indicate that as the income distribution of an MSA becomes more unequal, we can expect an increase in the proportion of tracts suffering from poverty concentration. However, when the model is limited to measuring only extreme-poverty tracts (40%+), the Gini coefficient is no longer statistically significant. This indicates that such extreme levels of poverty concentration cannot be accounted for in any meaningful way by the overall income distribution of an MSA.

It is also worth noting that the racial component is only significant in the 20%+ model, which presents a challenge to the conventional wisdom of racial tensions and preferences for homogenous communities leading to higher levels of poverty concentration. This trend indicates that when higher thresholds for concentrated poverty are employed, the racial composition of the MSA can no longer account for a significant portion of the poverty concentration level.

As a robustness check, I examine the same models using federally funded highways running with *four miles* of the central business district (see Table II, Appendix). Intuitively, a highway ray leading from the periphery of the MSA to within 4 miles of the central city would still provide a reasonable mechanism for the lowering of commuting times and the increase in available residential land, and therefore this measure can help to confirm the previous results. As expected, the level of statistical significance for each threshold remains the same, and the coefficients are very similar for all variables in the model.

2. Alternative Highway Measures, Time-Invariant Variables, & Year Dummies

In Table III, I further examine the robustness and appropriateness of the previous results by employing Fixed Effects panel regressions, but instead of using rays within 1 mile (or 4 miles) of the central business district, I use two alternative measures of urban transportation infrastructure that cause suburbanization. The first alternative measure includes all federally funded highways in an MSA. This is a check to see if access to the central business district is a necessary condition for highway expansion to initiate a process of suburbanization. The second alternative measure is simply the mileage of federally funded interstate highways running through the central city, which provides an alternative way of measuring the concept of highway introduction. The results of these new models, which are presented in Table III below, largely confirm the results of the earlier panel regressions. In the interest of length, the table only displays results for the 40%+ model that the author privileges due to its issue salience; results for the 20%+ and 30%+ models can be found in Tables IV and V in the appendix.

While model (1) shows that the total number of highways in an MSA has a coefficient of .335 and is a statistically significant at .001 level, model (2) shows that highway expansion is *not* statistically significant when represented in total mileage instead of rays. This is probably due to the fact the existence of the access route to outlying suburban areas is more important than the actual mileage of coverage, which would mean the additional (marginal) mile constructed would not have a strong effect and may depend on other factors such as overall MSA population density. In both models, the Gini coefficient and the percentage of the population that is black remain statistically insignificant.

As a final robustness check, Table VI (Appendix) include year dummies in Fixed Effects models to account for the possibility that my highway measures are not capturing non-MSA specific changes that have occurred over time, such as technological advancements or fluctuations in gas prices. Each model employs a different measure of highway expansion, and both remain positive and statistically significant predictors of poverty concentration, although they do lower the coefficients. While this is a useful

Table III

Panel Regressions with Fixed or Random Effects (1960-1990): Models of Change in Poverty Concentration Examining Alternative Measures of Highway Expansion or Time-Invariant Variables

All three models employ a 40%+ threshold (for 20%+ or 30%+, See Appendix Tables IV & V)	(1) MSA Rays (FE)	(2) CC Mileage (FE)	(5) 1-mile CC Rays (RE)
Federally Funded Rays in MSA	0.335***		
	[0.0666]		
Natural Log of Population	3.279***	4.025***	0.498*
	[0.500]	[0.510]	[0.199]
MSA Poverty Rate (%)	1.033***	1.017***	1.076***
	[0.0474]	[0.0480]	[0.0342]
Simulated Gini Coefficient	-16.50	-13.03	7.941
	[9.644]	[9.831]	[7.029]
Pct of Pop Black	-0.0103	0.0286	0.0254
	[0.0584]	[0.0590]	[0.0205]
Miles of CC Federally Funded Highways		0.00655	
		[0.00368]	
Central City Interstate Rays, 1-mile Definition			0.355**
			[0.108]
Northeast Region Dummy			2.429***
			[0.604]
Midwest Region Dummy			3.190***
			[0.521]
South Region Dummy			0.0760
			[0.584]
MSA within 25 miles of Coastline or National Border (binary)			0.790*
			[0.386]
Constant	-45.69***	-55.89***	-21.35***
	[6.903]	[7.115]	[3.859]
Observations	932	932	932
Adjusted R-squared	0.269	0.246	

Standard errors in brackets *Note: West Region Omitted*
* p<0.05 ** p<0.01 *** p<0.001

robustness check, these models are problematic and should not be preferred, as the year dummies are highly correlated with the highway measures used here. Due to this multicollinearity, it is difficult to disentangle the effect of highways versus the effects of the year dummies, and this confounds our ability to interpret the OLS results.

Finally, I use panel regressions with Random Effects in models (5) and (6) in order to evaluate the impact of several time-invariant MSA features that I hypothesized earlier may impact poverty concentration. Fixed Effects models allows for correlations of omitted variables with latent individual effects without biasing the coefficient estimate, and thus it imposes that condition on the regression. This prevents the comparison of time-invariant variables across entities (i.e., MSA's). To use Random Effects, we must assume that each MSAs error term is not correlated with the independent variables; the Hausman test (see Appendix I) showed that this assumption is rejected, so the coefficients are likely biased under Random Effects models. However, for the purposes of analyzing our additional dummy variables, I employ Random Effects conditions anyway.

The results for the Random Effects models mirror the results thus far, with the coefficient signs and statistical significance remaining consistent for each variable. While Random Effects considers both cross-sectional and unit-specific time variation in its estimations, the dummy variables have a slightly more nuanced interpretation. Given their time-invariant nature, their coefficients represent only the effect of change *across units* rather than over time. For this reason, the coefficients represent the region-specific incidence of poverty concentration prior to the introduction of the federal highway system. Land Use Theory would predict that MSAs closer to coasts and borders would have lower rates of poverty concentration, because these exogenous boundaries of metropolitan sprawl and population decentralization would be expected to limit opportunities for residential segregation. However, the coefficient on the dummy variable for cities within 25 miles of a coast or national border was actually positive in all the models in which the coefficient statistically significant, indicating that those cities closer to these boundaries are likely to have higher proportions of poverty concentration, ceteris paribus.

The regional dummy coefficient estimates are in line with expectations based on historical patterns of United States urbanization. Given that MSAs developed more extensively in the Northeast and Midwest regions prior to WWII than did the cities of South or West Regions, we expect that they would have higher rates of poverty concentration, given the formation of immigrant/ethnic neighborhoods and working-class neighborhoods in the wake of industrialization. Compared to the omitted West region, the Northeast had a coefficient of approximately 2.4 in both models, while the Midwest had a coefficient of approximately 3.0; the South region is statistically insignificant. These results indicate the we should expect the percentage of tracts with poverty concentration to be 2.4 points higher in the Northeast and 3 points higher in the Midwest when compared to the West.

3. Instrumental Variable Regressions: Panel & Long-Difference

This analysis concludes with a set of long-difference and panel IV regressions, regressing the overall change in poverty concentration in an MSA on the overall change in each of the covariates in our model. In table VII below, Model (1) shows the results of the first-stage regression, in which change in log central city population (i.e., centralization or decentralization) is instrumented for using the change in the stock of central city highway rays and the change in median family income, resulting in an R^2 equal to 0.35. Models (2) through (4) validate the results of the earlier panel regressions, showing that highway expansion is a statistically significant predictor of poverty concentration in 30%+ and 40%+ threshold models, even when using long differences; highways remain statistically insignificant in the 20%+ model.

Table VII

Long-Difference & Panel IV Regressions (1960-1990) - Instrumenting Change in CC Population using Change in Median Family Income and Rays w/in 1 mile of the Central Business District (CBD)

		Long-Difference		Panel
	(1)	(2)	(3)	(4)
	1st Stage	40%+	40%+	40%+
Median Family Income	0.0000455***			
	[0.00000419]			
Central City Interstate Rays, 1-mile definition	-0.0334***			
	[0.00906]			
Natural Log of CC Population		-5.321*	-5.316*	-8.467***
		[2.326]	[2.401]	[2.199]
MSA Poverty Rate (%)		1.213***	1.213***	0.995***
		[0.0880]	[0.0880]	[0.0513]
Natural Log of Population		3.140	3.168	9.936***
		[1.857]	[2.002]	[1.501]
% Black of Population		-0.289**	-0.287**	-0.0143
		[0.103]	[0.105]	[0.0640]
Simulated Gini Coefficient		-104.9**	-104.0**	-61.00***
		[35.95]	[35.95]	[16.73]
MSA Population <100,000 Dummy			0.0623	
			[0.695]	
Constant	0.236***	3.779***	3.707***	-13.68
	[0.0364]	[0.725]	[1.029]	[14.21]
No. of Observations	240	216	216	932
Adjusted R-squared	0.350	0.445	0.443	

Standard errors in brackets
* p<0.05 ** p<0.01 *** p<0.001

In Long-Difference model (2), a one standard deviation decrease in the log of central city population—a decline of approximately 1%—is associated with a 5.38-point in the percentage of tracts suffering poverty concentration. Model (3) adds a dummy variable to the Long-Difference model for whether an MSA's population was below 100,000 in 1950 in order to determine if the explanatory variable is robust when considering only metropolitan areas with a "critical mass" to begin large-scale suburbanization; the dummy was not significant at the .05 level and did not affect the significance or magnitude of the coefficient on central city population. In the panel regression, a decrease of one standard deviation in central city population causes an approximately 8.5-point increase in the percentage of MSA tracts with poverty rates above 40%. These results clearly indicate that suburbanization leads to more concentrated poverty, at least during the 1960-1990 period of interstate highway expansion.

Interestingly, in these Long-Difference and Panel models, the Gini coefficient is now a statistically significant determinant of poverty concentration, even though it was insignifcant in almost all of the Fixed Effects and Random Effects panel regressions for the 40%+ threshold models. Similarly, the black percentage of the population now appears significant when included in Long-Difference regressions, although it remains insignificant in the Panel regression using instrumented variables. However, more theoretical work is required to understand the effect of these variables, as neither variable has the expected sign in these models. We would expect that higher proportions of black citizens and higher Gini coefficients—i.e., more lopsided distributions of income—would lead to greater demand for suburbanization and thus higher rates of poverty concentration, and yet both variables have a negative relationship with poverty concentration rather than a positive one. This negative coefficient on for the simulated Gini coefficient could be an indication of a methodological error in the creation of the variable, which only captures changes in relative wage rates across industries and not changes in employment shares. Given that particular metropolitan areas—as well as the United States as a whole—have likely experienced economic restructuring over the decades, the Gini coefficient used here may not capture the full effect of the underlying income distribution. Additionally, while an extensive literature on racial and ethnic factors already exists in urban economics, it would be useful to more thoroughly understand the effect of local or regional income distributions on poverty concentration.

VI. Conclusion

To summarize, these results clearly indicate that rays running through a central city—and the number of MSA highways *overall*—has a positive causal relationship with poverty concentration. The coefficient on the primary explanatory variable—whether a highway measure or an instrumented central city population measure—was statistically significant for at least the .05 level in all but one of 40%+ and 30%+ thresholds models, and in most cases it was significant at .001 level. As expected, the models using the 20%+ poverty threshold were rarely statistically significant, indicating that tracts (i.e., neighborhoods) that fit this categorization are formed by a different set of mechanisms and determinants than the more extreme poverty cases.

The results of the empirical analysis undertaken in this paper have established a robust causal connection between Federal Highway System expansion and poverty concentration. Accordingly, since we have strong theoretical reasons to believe that highway transportation networks increase both the demand for and supply of land for suburbanization, it has been argued here that it is the residential segregation induced by suburbanization that has led to increases in poverty concentration. Across the multitude of poverty concentration models established, and across the various measures of highway expansion employed, the result remains robust—as highway systems allow for decentralization in metropolitan areas, we can expect to see more neighborhoods suffering from concentrated poverty. Moreover, these models account for a significant proportion of the variation in poverty concentration rates, furthering the case for the importance of suburbanization processes as a concern in urban economics.

However, there are several limitations of this analysis that provide opportunities for future research. For instance, because the tracts in these data were not coded for whether they were inside the central city or in the surrounding area, there remains an opportunity to investigate the differential rates of poverty concentration across the various areas of an MSA, rather than examining its poverty distribution as a whole. Also, limitations in demographic data precluded the possibility of studying additional racial groups that may affect residential segregation, such as Hispanics.

Additionally, I advocate for further investigation of the forces of suburbanization and their impact on poverty concentration. For instance, the creation of public housing and the availability of mortgage subsidies—both significantly influenced by federal policy—are likely to have significant effects on the supply of suburban residences and the demand for such housing. This could provide further insight into how economic and social policies shape the incentives for different types of residential development and neighborhood formation. It may also be worthwhile to investigate processes of gentrification to see if these influxes of wealthy residents and rising property values in urban areas is ameliorating or exacerbating the problem of poverty concentration. If these processes can become better understood, it would be possible to predict and prevent potentially deleterious urban environments such as communities afflicted with debilitating levels of poverty.

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VIII. Appendix

1: Hausman Test

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
        racc |    .4798277     .3315916        .1482361        .0804065
PovertyRat~t |     1.02747     1.010276         .017194        .0327726
       ginih |   -15.17011    -1.249924       -13.92019        6.689096
      pctblk |    .0238046    -.0113884         .035193        .0551852
      logpop |    3.835624      .621058        3.214566        .4338119
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       79.17
                Prob>chi2 =      0.0000
```

2: Table II

Table II						
Panel Regressions with Fixed Effects, 1960-1990: Determinants of Poverty Concentration Growth in Metropolitan Statistical Areas (MSAs)						
	Models Using Federally Funded Highway Rays within 1 mile of Central City			Models Using Federally Funded Highway Rays within 4 miles of Central City		
	Coefficients represent change in % of Tracts with a Poverty Rate above a certain threshold (40%+, 30%+, or 20%+) in an MSA					
	(1)	(2)	(3)	(4)	(5)	(6)
	40%+	30%+	20%+	40%+	30%+	20%+
Central City Interstate Rays, 1-mile definition	0.480***	0.654***	0.459			
	[0.138]	[0.169]	[0.257]			
Natural Log of Population	3.836***	5.455***	6.907***	3.402***	4.996***	6.869***
	[0.480]	[0.585]	[0.891]	[0.487]	[0.594]	[0.913]
MSA Poverty Rate (%)	1.027***	1.625***	2.790***	1.037***	1.635***	2.790***
	[0.0478]	[0.0583]	[0.0888]	[0.0474]	[0.0579]	[0.0889]
Simulated Gini Coefficient	-15.17	41.30***	123.5***	-14.13	43.19***	125.8***
	[9.755]	[11.90]	[18.10]	[9.588]	[11.71]	[17.98]
Black % of Population	0.0238	0.0857	0.308**	0.0212	0.0852	0.315**
	[0.0582]	[0.0710]	[0.108]	[0.0575]	[0.0702]	[0.108]
Central City Interstate Rays, 4-mile definition				0.581***	0.719***	0.348
				[0.113]	[0.138]	[0.212]
Constant	-53.27***	-97.91***	-152.7***	-48.75***	-93.44***	-153.2***
	[6.648]	[8.108]	[12.34]	[6.611]	[8.075]	[12.40]
N	932	932	932	932	932	932
adj. R-sq	0.255	0.442	0.523	0.270	0.452	0.522

Standard Errors in Brackets
* p<0.05 ** p<0.01 *** p<0.001

3: Table IV

Table IV

Panel Regressions with Fixed Effects, 1960-1990: Using Alternative Measures of Federally Funded Highway Expansion as Determinants of Poverty Concentration Growth

	(1)-(3): Using All Federally Funded Highway Rays in MSA			(4)-(6): Using All Federally Funded Highway Mileage in Central City		
	Coefficients represent change in % of Tracts with a Poverty Rate above a certain threshold (40%+, 30%+, or 20%+) in an MSA					
	(1)	(2)	(3)	(4)	(5)	(6)
	40%+	30%+	20%+	40%+	30%+	20%+
federally funded rays in MSA	0.335***	0.483***	0.275*			
	[0.0666]	[0.0808]	[0.125]			
Natural Log of Population	3.279***	4.604***	6.535***	4.025***	5.391***	6.951***
	[0.500]	[0.606]	[0.935]	[0.510]	[0.620]	[0.941]
MSA Poverty Rate (%)	1.033***	1.633***	2.792***	1.017***	1.614***	2.781***
	[0.0474]	[0.0575]	[0.0886]	[0.0480]	[0.0584]	[0.0886]
Simulated Gini Coefficient	-16.50	39.01***	123.1***	-13.03	42.26***	124.7***
	[9.644]	[11.70]	[18.04]	[9.831]	[11.96]	[18.15]
Black % of Population	-0.0103	0.0348	0.283**	0.0286	0.0794	0.307**
	[0.0584]	[0.0709]	[0.109]	[0.0590]	[0.0718]	[0.109]
miles of CC federally funded highways				0.00655	0.0138**	0.00835
				[0.00368]	[0.00448]	[0.00680]
Constant	-45.69***	-86.30***	-147.7***	-55.89***	-96.78***	-153.2***
	[6.903]	[8.375]	[12.92]	[7.115]	[8.656]	[13.14]
Observations	932	932	932	932	932	932
Adjusted R-squared	0.269	0.458	0.524	0.246	0.438	0.522

Standard Errors in Brackets
* p<0.05 ** p<0.01 *** p<0.001

4: Table V

Table V

Panel Regressions with Random Effects (1960-1990) - Examining Time-Invariant Determinants of Poverty Concentration Growth

	(1)-(3): Interstate Highway Rays within 1 mile of CC			(4)-(6): Interstate Highway Rays within 4 miles of CC		
	Coefficients represent change in % of Tracts with a Poverty Rate above a certain threshold(40%+, 30%+, or 20%+) in an MSA					
	(1)	(2)	(3)	(4)	(5)	(6)
	40%+	30%+	20%+	40%+	30%+	20%+
Central City Interstate Rays (1 mile definition)	0.355**	0.642***	0.443*			
	[0.108]	[0.137]	[0.179]			
Natural Log of Population	0.498*	0.915***	0.735*	0.297	0.760**	0.703*
	[0.199]	[0.257]	[0.305]	[0.189]	[0.246]	[0.291]
MSA Poverty Rate (%)	1.076***	1.739***	2.718***	1.087***	1.752***	2.727***
	[0.0342]	[0.0437]	[0.0552]	[0.0340]	[0.0434]	[0.0552]
Simulated Gini Coefficient	7.941	44.61***	63.97***	5.504	42.23***	62.11***
	[7.029]	[8.937]	[11.56]	[6.971]	[8.860]	[11.58]
Pct of Pop Black	0.0254	0.0415	0.108***	0.0270	0.0445	0.110***
	[0.0205]	[0.0268]	[0.0300]	[0.0203]	[0.0266]	[0.0299]
Northeast Region Dummy	2.429***	4.295***	4.713***	2.373***	4.166***	4.600***
	[0.604]	[0.795]	[0.876]	[0.599]	[0.788]	[0.871]
Midwest Region Dummy	3.190***	4.955***	4.259***	2.954***	4.579***	4.014***
	[0.521]	[0.687]	[0.750]	[0.518]	[0.682]	[0.748]
South Region Dummy	0.0760	0.812	-0.164	-0.00322	0.667	-0.262
	[0.584]	[0.769]	[0.844]	[0.580]	[0.763]	[0.842]
MSA within 25 miles of Coastline or National Border (binary)	0.790*	1.032*	-0.00445	1.020**	1.327**	0.148
	[0.386]	[0.510]	[0.554]	[0.387]	[0.510]	[0.559]
center city interstate rays (4 mile definition)				0.541***	0.777***	0.477**
				[0.0931]	[0.118]	[0.159]
Constant	-21.35***	-45.33***	-52.14***	-18.63***	-43.27***	-51.44***
	[3.859]	[4.951]	[6.127]	[3.765]	[4.826]	[6.053]
Observations	932	932	932	932	932	932
Adjusted R-squared						

Standard errors in brackets

* p<0.05 ** p<0.01 *** p<0.001

Note: West Region Omitted

5: Table VI

Table VI

Panel Regressions with Fixed Effects & Year Dummies (1960-1990): Determinants of Poverty Concentration Growth, controlling for non-MSA Specific Time Effects

	(1)-(3): Using Interstate Highways within 4 miles of CC as Measure of Highway Expansion			(4)-(6): Using All Federally Funded Rays in MSA as Measure of Highway Expansion		
	Coefficients represent change in % of Tracts with a Poverty Rate above a certain threshold(40%+, 30%+, or 20%+) in an MSA					
-	(1)	(2)	(3)	(4)	(5)	(6)
	40%+	30%+	20%+	40%+	30%+	20%+
Central City Interstate Rays (4-mile definition)	0.366**	0.0793	-0.247			
	[0.132]	[0.154]	[0.248]			
Natural Log of Population	0.226	-1.013	1.812	0.0769	-1.069	1.894
	[0.750]	[0.874]	[1.406]	[0.751]	[0.873]	[1.406]
MSA Poverty Rate (%)	1.019***	1.593***	2.713***	1.020***	1.596***	2.714***
	[0.0494]	[0.0576]	[0.0926]	[0.0495]	[0.0576]	[0.0927]
Simulated Gini Coefficient	-46.53**	3.638	115.4***	-51.28**	1.426	117.6***
	[16.08]	[18.73]	[30.12]	[16.14]	[18.76]	[30.23]
Black % of Population	-0.0796	-0.109	0.131	-0.0986	-0.119	0.139
	[0.0583]	[0.0679]	[0.109]	[0.0587]	[0.0682]	[0.110]
1970 Year Dummy	0.424	1.685***	1.388*	0.465	1.565***	1.259*
	[0.292]	[0.340]	[0.547]	[0.289]	[0.336]	[0.541]
1980 Year Dummy	1.702***	4.012***	3.834***	1.708***	3.852***	3.702***
	[0.346]	[0.403]	[0.648]	[0.350]	[0.407]	[0.656]
1990 Year Dummy	2.322***	4.535***	3.500***	2.431***	4.415***	3.312***
	[0.534]	[0.622]	[1.000]	[0.524]	[0.609]	[0.982]
Federally Funded Rays in MSA				0.205**	0.114	-0.0823
				[0.0785]	[0.0913]	[0.147]
Constant	3.699	-1.918	-83.62***	7.607	-0.404	-85.72***
	[12.86]	[14.98]	[24.09]	[12.87]	[14.96]	[24.11]
Observations	932	932	932	932	932	932
Adjusted R-squared	0.306	0.527	0.547	0.306	0.528	0.547

Standard errors in brackets
* p<0.05 ** p<0.01 *** p<0.001

6: Table VIII

Table VIII

Long Difference IV Regressions (1960-1990) - Instrumentation of Change in CC Population using Change in Median Family Income and Highway Rays w/in 1 mile of CC

	(1) 1st Stage	(2) 40%+	(3) 30%+	(4) 20%+	(5) 40%+
Median Family Income	0.0000455***				
	[0.00000419]				
Central City Interstate Rays, 1-mile definition	-0.0334***				
	[0.00906]				
Natural Log of CC Population		-5.321*	-9.133***	-4.142	-5.316*
		[2.326]	[2.726]	[4.630]	[2.401]
MSA Poverty Rate (%)		1.213***	1.656***	2.792***	1.213***
		[0.0880]	[0.103]	[0.175]	[0.0880]
Natural Log of Population		3.140	4.047	3.941	3.168
		[1.857]	[2.176]	[3.697]	[2.002]
% Black of Population		-0.289**	-0.249*	0.0239	-0.287**
		[0.103]	[0.120]	[0.204]	[0.105]
Simulated Gini Coefficient		-104.9**	-114.2**	75.67	-104.0**
		[35.95]	[42.12]	[71.55]	[35.95]
MSA Population <100,000 Dummy					0.0623
					[0.695]
Constant	0.236***	3.779***	6.195***	3.806**	3.707***
	[0.0364]	[0.725]	[0.850]	[1.443]	[1.029]
Observations	240	216	216	216	216
Adjusted R-squared	0.350	0.445	0.531	0.624	0.443

Standard errors in brackets
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

7: Table IX

Table IX

Two Stage Least Squares IV Panel Regressions (1960-1990): Instrumentation of Change in CC Population using Change in Median Family Income and Highway Rays w/in 1 mile of CC

	(1) 40%+	(2) 30%+	(3) 20%+
Natural Log of CC Population	-8.467***	-10.25***	-11.49**
	(2.199)	(2.667)	(3.957)
Simulated Gini Coefficient	-61.00***	-13.48	59.39*
	(16.73)	(20.29)	(30.10)
% Black of Population	-0.0143	0.0429	0.248*
	(0.0640)	(0.0776)	(0.115)
Natural Log of Population	9.936***	12.94***	14.94***
	(1.501)	(1.821)	(2.702)
MSA Poverty Rate (%)	0.995***	1.583***	2.751***
	(0.0513)	(0.0622)	(0.0923)
Constant	-13.68	-51.33**	-95.43***
	(14.21)	(17.24)	(25.57)
Observations	932	932	932
R-squared	0.1677	0.3306	0.5856

Standard errors in parentheses
* p<0.05 ** p<0.01 *** p<0.001