Income Distribution, City Size, and the Role of Public Transportation

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by

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This article presents an income inequality analysis for all 1990 U.S. metropolitan statistical areas (MSAs). The analysis is concerned with whether public transportation has a detectable influence on levels of urban income equality. Because public transportation systems are generally designed to link residences with employment locations, higher levels of transit service provision, all other factors being equal, should be associated with higher employment rates and more uniform distributions of economic gains. The research presented here was influenced by an analysis originally performed by Haworth, Long, and Rasmussen (1978). Along with there study, few analyses have tried to evaluate policies that affect income distribution. The results of this analysis provide a macroscopic view of the efficiency and effectiveness of urban transportation investments with respect to urban income inequality.

INTRODUCTION

Evidence shows that the level of income inequality in the U.S. is increasing. These trends suggest that not only is the problem worsening in the U.S., but that the U.S. ranks at the bottom compared to other industrialized countries (McFate 1991). Trends at the national level are symptomatic of income distribution disparities at the state, regional, and local levels and have far-reaching social and economic implications (Galbraith 1998). The Kerner Commission reported that income inequality played a significant role in the civil unrest experienced during the 1960s (National Advisory Commission on Civil Disorders 1968). Today, indicators suggest that the U.S. is enjoying robust economic prosperity with sharp declines in reliance on welfare, low levels of unemployment, optimistic capital markets, and surging corporate profits. On the other hand, there is evidence of increasing poverty levels, shrinking health care coverage, declining real wages, and unstable employment related to corporate restructuring. Thirty years after the Kerner Commission reported that the U.S. is becoming "two separate societies…", income data suggest that the gap between rich and poor is becoming more pronounced (Milton S. Eisenhower Foundation 1998).

Naturally, these national trends are rooted in the social, economic, and political conditions of our urban and metropolitan areas. Research stretching over the past fifty years has focused on how national and urban income distributions are influenced by the size and rate of development. For urban areas, "development" encompasses the composition and scale of economic activities as well as population settlement. Influenced by Kuznets' (1955) research on national development and subsequent research on urban income distribution by Duncan and Reiss (1956), Richardson (1973), Farbman (1975), and Danziger (1976), Haworth, Long, and Rasmussen (1978) analyzed income distribution as a function of metropolitan size and population growth rates. Using a sample of 79 SMSAs with 1970 populations over 250,000, they reported that size and growth rates were positively associated with measures of income inequality. Their interpretation of these results comprised the "monopoly hypothesis" which attributed increasing income inequality to capital accumulation by the upper income classes by stating, "increases in [city] size and growth raise the monopoly rents earned by those who are insulated from competition" (Haworth, Long, and Rasmussen 1978, p.3). The results of their empirical analysis initiated a debate over the observed relationship between urban development and income distribution.

Others have provided explanations for the correlation between urban income inequality and population size, but there is no general agreement on the causes. Some explanations focus on shifting labor demand as urban areas increase in size. With increased size, urban economies become more specialized, accentuating wage differentials between skilled and unskilled labor (Alperovich 1995). Some argue that labor supply conditions play a prominent role in the structure of income distribution. The in-migration of low-skilled workers seeking greater economic opportunities bid down wage rates at the lower levels, leading to increased differences in income allocations (Farbman 1975; Haworth, Long, and Rasmussen 1978; Hirsch 1982). An underlying, while not explicitly stated, explanation includes racial discrimination. Discrimination has direct and indirect implications on labor conditions in terms of skill/education levels, job opportunities, and potential for advancement (i.e., higher wages) (Betz 1972). Detecting the impacts of racial discrimination on income distribution is complex due to the far-reaching social implications that are not easily quantified. Analyses of urban income inequality have generally attempted to describe cross-sectional trends, while controlling for labor supply, labor demand, social, and demographic factors.

Previous Research

Relatively similar methodologies have been used for urban income distribution analyses. Typically, ordinary least squares regression (OLS) is used with measures of income inequality as dependent variables. Income levels, industry mix, and other demographic characteristics are frequently used as explanatory variables. In some cases, regression models are estimated separately for MSA (or SMSA) population size to capture differential effects for small, medium, and large urban or metropolitan areas (see Kennedy and Nord 1984). In many cases regional identifiers (as dummy variables) are used to control for suspected regional differences in racial discrimination, industrial composition, and economic vitality. Additional studies have isolated income inequality effects by race (Nord 1984), gender (Soroka 1987), and age characteristics (Garofalo and Fogarty 1979). The independent variables receiving most attention are those for population size and growth rate.

It is possible to compare the results of previous research given that the regression model specifications are nearly identical. The studies identified in Table 1 are for analyses that used a Gini concentration ratio (Gini ratio) as a measure of urban income inequality. Other analyses, although few in number, were excluded because they used alternative measures of income inequality (discussed later). With the exception of Farbman (1975) and Nord (1980), the results of these analyses suggest that there is a significant, positive relationship between population size and urban income inequality. In Nord's 1980 study, however, he estimated separate equations for population size categories. While income inequality declined with population size for cities with less than 50,000 persons, the coefficient was significant and positive for SMSAs with greater than 250,000 persons. Among the other studies, the coefficients for population size were consistently between 0.0003 and 0.003. The coefficients for population growth rate were less consistent predictors of income equality with mixed results for sign as well as significance level.

Table 1 Previous urban income inequality studies with Gini ratio as dependent variable (adapted from Nord 1980)

Author(s)	Year	N	Specification	Range of City Size	Years Analyzed	Pop. Size Regression Coefficient	Pop. Growth Rate Coefficient	Other factors (variables)
Farbman	1975	208	linear	50,000-150,000	1960	-0.01700 **	na	Demographic
				150,000-250,000		-0.10500 **	na	Demographic
				250,000-1,000,000		-0.00660 *	na	Demographic
Danziger	1976	212	linear	55,000-7,100,00	1960	-0.00200	na	Demographic, regional
			quadratic	55,000-7,100,00		0.00860	na	
Haworth et al	1978	79	linear	over 250,000	1970	0.00043 **	0.00037 *	Typical
Garofalo and Fogarty	1979	125	linear	over 250,000	1970	0.0033697 **	0.1845 *	Typical
Nord	1980	522	linear	2,500-10,000	1970	-0.329 *	-0.473 *	Industrial mix
		193	linear	10,000-50,000		-0.027 *	-0.286 *	Industrial mix
		28	linear	SMSAs		0.116 *	0.279 *	Industrial mix
Haworth et al	1982	79	linear	over 250,000	1970	0.00027 **	0.00039 *	Industrial mix
Hirsch	1982	124	linear	over 250,000	1970	0.00042 **	-0.000024	Industrial mix
Kennedy and Nord	1984	167	linear	over 50,000	1950-60-70	0.00207 *	0.10972 *	Demographic
Soroka	1987	59	linear	over 25,000	1970	0.00790 **	0.1237	Demographic, male/female
					1980	0.54780 *	0.1827	comparison
Galster, McCorkhill, and Gopalan	1988	120	linear	SMSAs	1980	0.970	na	Demographic, industrial mix
			quadratic			-0.400	na	
Chakravorty	1996	134	linear	over 250,000	1990	0.0023677 **	-0.000264 **	Demographic
Cloutier	1997	216	linear	over 250,000	1979/89	0.00400 **	0.005	Industrial mix

* denotes significant at $p < 0.05$, ** denotes significant at $p < 0.01$

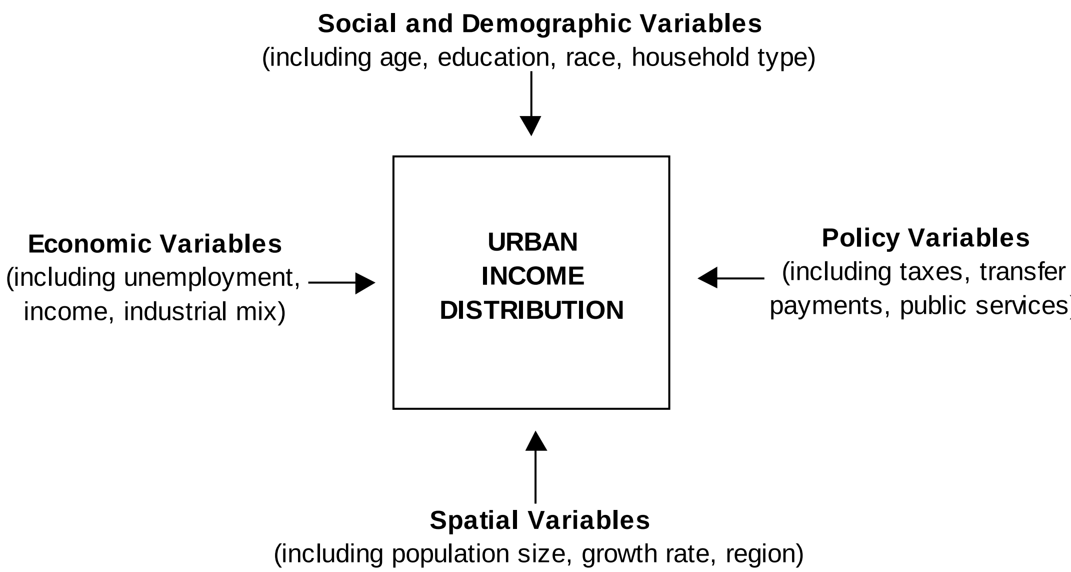
Income Inequality Measures

The Gini ratio is a traditional measure of income inequality (Gillis, Perkins, Roemer, and Snodgrass 1992; Paglin 1975). The Gini ratio estimates the degree to which the income distribution for a population varies from absolute equality. The Gini ratio is the relationship between the cumulative proportion of population (CPP) and the cumulative proportion of income earned (CPIE). Plotting CPP versus CPIE for an equal income distribution produces a 45-degree line. Unequal income distributions result in a more curved line (i.e., Lorenz curve), with the difference in areas between the line of equality and the Lorenz curve indicating the degree of income inequality. A ratio of zero indicates a perfectly equal income distribution, while a ratio of one indicates the highest level of inequality.

While the Gini ratio is an accepted measure for estimating income inequality, some argue that although it quantifies the level of inequality, it fails to indicate the structure of inequality and account for other lifecycle dynamics (Paglin 1975; Garofalo and Fogarty 1979). In other words, the Gini ratio does not express how incomes are concentrated by class or income category. Alternative measures that have been used in income distribution analyses include the percent of income within percentile rankings (Garofalo and Fogarty 1979), poverty rates (Haworth, Long, and Rasmussen 1979), median income levels (Danziger 1976), and income ratios (Nord 1984). Some income ratios include white to non-white (Nord 1984), male to female (Soroka 1987), or percentile group comparisons (Cloutier 1997). These measures indicate the degree of disparity among two subgroups of the population. While ratios are useful measures for structural income inequality, they fail to provide an overall assessment of a population's income distribution, as does the Gini ratio. The current analysis relied on the Gini ratio as a measure of income inequality conforming to the studies shown in Table 1.

Chakravorty (1996) provided a conceptual framework for urban income distribution analysis. His analytical framework was drawn from an extensive review of prior literature and related four groups of factors from which variables are derived for quantitative analysis (see Figure 1). Of the four groups of variables, policy variables are most obviously missing from prior analyses. This is likely the case because social and demographic, economic, and spatial variables tend to be easier to quantify compared to policy variables (Chakravorty 1996). For this reason, the research on urban income inequality is descriptive and exploratory rather than a means of policy analysis. Currently the outcomes of prior research may address only policy issues related to perhaps educational services and economic development as they influence income distribution. Such analyses appear to be appropriate for assessing the long-term impacts of taxation, social services, and other public goods and services. With this in mind, an objective of the current study is to test the significance of public transportation as a public policy mechanism with possible implications for urban income inequality in the U.S.

Figure 1 Conceptual Framework (from Chakravorty 1996)



Public Transportation

One objective of public transportation services is to link workers with employment locations. Along with the transit network, origins (residential locations) and destinations (non-residential locations) create zones of travel demand and supply. In addition to considering observed travel patterns, transit routing can also take into account the propensity of residents to use transit for work and non-work related trip making (Black 1995). Demand tends to be a function of socio-economic characteristics most closely related to income levels (i.e., vehicle ownership rates) and population density. Limited transportation mobility is a contributing factor to unemployment for low-income persons. To address this problem, a variety of current efforts are focusing on improving mobility to help welfare recipients find and maintain employment (Sanchez 1999). It seems logical that if transportation mobility affects employment opportunities, then income levels should also be positively affected by transportation mobility. While other benefits such as time savings, reduced operating and capital costs can result from improved transit services (see Dajani and Egan 1974), the largest potential benefit for most low income persons would be the ability to consistently reach their workplace as well as conduct other daily affairs (e.g., shopping, health services, child care, recreation). In regard to transit subsidies, Frankena (1973) concluded that income inequality might only be slightly influenced by such policies because subsidies tend to be relatively small. His study considered only transit subsidies and not overall transit service provision.

Income effects of public transportation investments intimates transfer payments or subsidies. Because transit users and non-users contribute to system operations at varying rates through fares and taxes with no direct transaction linking payment with a market good, equity concerns often arise (Black 1995). In 1969, Altshuler argued that mobility inequality is strongly tied to income inequality, producing detectable negative social impacts (Altshuler 1969). Nearly thirty years later, the issue of mobility continues to be cited as a major social and economic problem (Wilson 1997). However, given the low modal share of transit in the U.S., it is likely that many low income persons will need to directly benefit from improved public transit for there to be a significant impacts. The degree of income redistribution resulting from mobility increases will be greatly dependent on the efficiency of service delivery by transit providers (Black 1995). Inefficient transit service delivery will absorb potential income benefits.

METHODOLOGY

Most previous analyses rely on OLS regression to predict measures of urban income inequality. Specifications tend to be linear, except in the cases of the population size, population growth rate, and income variables where squared terms are introduced (Danziger 1976). While many researchers note the interaction among variables most commonly used to predict urban income inequality, few have accounted for these effects within their specifications. Danziger (1976) and Galster (1988) were the only examples where a system of equations was used to predict income inequality. Nearly all other authors describe how income distributions are simultaneously determined by other economic, social, and demographic variables, however, with the exception of Danziger and Galster; all treat income levels as exogenous variables. Similar to Danziger and Galster, the model presented here employs a system of equations (two-stage least squares - 2SLS) to predict urban income distributions. The model specifies three endogenous variables influenced by previous urban income distribution analyses and by Galster's (1998) econometric model of urban opportunity. The following is a brief description of the variables included.

Table 2 Regression variables

Name	Description
GINI	Gini concentration ratio based on 1990 income (dependent)
AREA	Geographic size of MSA (square miles)
CRIMEPC	Serious crimes reported per capita
DENSITY	Population density
EMPPC	Full time equivalent workers (weighted by average weeks worked - see Galster 1998)
FEMHEAD	Proportion of female headed households with children
FEMHEAD	Proportion of female headed households with children (predicted)
HINDEX	Home price index (percent of mean from all MSAs)
INCOME	Median household income
INCOME	Median household income (predicted)
JOBSPC	Number of jobs per 100 population aged 15 to 64
MFRATIO	Male to female ratio (ages 15 to 64)
PAGRI	Proportion of persons employed in agriculture
PCAROWN	Proportion of household owning automobiles
PCOLL	Proportion of persons over 25 years with college degree or higher
PFIRE	Proportion of persons employed in finance, insurance, or real estate
PM15_64	Proportion of population that is male, ages 15 to 64
PMANUF	Proportion of persons employed in manufacturing
POP1990	Population in millions
POPGROW	Population growth rate from 1970 to 1990
PTRANSIT	Proportion of persons using transit for work commute
PWELFARE	Proportion of households receiving welfare payments in 1989
PWHITE	Proportion of population that is white
RINDEX	Rental price index (percent of mean from all MSAs)
TRANSITC	Transit capacity/density (directional miles per 100 square miles)

Note: All data is from 1989, 1990, or 1991 sources. Bold indicates endogenous variables.

As previously mentioned, there are four primary groups of factors that influence urban income distribution: social and demographic, economic, spatial, and public policy. Average household income levels are typically considered an important factor affecting the distribution or concentration of income. Most studies have specified income as an exogenous variable when most agree that the variation of average (or median) incomes between metropolitan areas is a function of labor supply and demand characteristics. This includes the mix of industry types, scale of industry, labor pool characteristics, along with other metropolitan factors that influence economic output (see Table 2 for variable definitions). The first stage equation to estimate household income levels was:

INCOME = *f* (EMPPC, JOBSPC, FEMHEAD, PWELFARE, PM15_64, PAGRI, PMANUF, PFIRE, PWHITE, PCOLL, HINDEX, RINDEX, POP1990)

The prevalence of female-headed households in urban areas is closely related to many interacting social and economic characteristics. The presence of single parent households typically indicates a variety of hardship conditions with implications for labor force participation, educational attainment, residential mobility, and crime (Galster 1998). Consequently, female-headed households are more likely to be welfare recipients, most notably for non-whites in central city residential locations. Persisting economic difficulties for these types of families are barriers to social and economic mobility, which limit their chances to improve their economic status. It has also been found that children from single parent households are more likely to exposed to drugs, crime, and experience unstable marriages later in life (Hogan and Kitagawa 1985; Spain and Bianchi 1996). The following equation is used to predict the proportion of female-headed households in metropolitan areas.

FEMHEAD = *f* (EMPPC, JOBSPC, PWELFARE, PAGRI, PMANUF, PWHITE, PCOLL, HINDEX, RINDEX, PFIRE, MFRATIO, CRIMEPC, DENSITY, POP1990)

Urban population sizes and growth rates are treated as exogenous variables in the regression equation specified here. While it has been argued that there may be a non-linear relationship between population size and income distribution, none of the previous empirical research has obtained statistically significant coefficients for non-linear terms (see for example Galster 1988; Danziger 1976). For this reason, it is assumed that there was a linear relationship between population size and income distribution. In addition, the percentage increase in population size over the twenty-year period from 1970 to 1990 was also used as an exogenous variable. No alternative measures have been used in previous studies that account for short term economic cycles that influence population and business location patterns.

In addition to determining whether urban population size has an affect on income inequality, this research tests the influence of public transportation supply on income inequality. The previous literature has essentially ignored public policy variables, which decreases the relevance of research results for planning and policy-making purposes. The role of public transportation services is endogenously determined because of the dynamic relationship between supply and demand. There can be no observed demand for public transportation without current services being provided. In addition, there is ample evidence that the social, economic, and spatial characteristics of urban areas have an impact on public transit ridership levels. Transit is more likely to be provided and used in more densely populated urban areas that have more centralized concentrations of employment (Hendrickson 1986). Many of the same variables that have been shown significant in predicting urban income distribution are also significant to transit ridership levels. For the reason, transit supply was specified as an endogenous variable as follows:

TRANSITC = *f* (INCOME, PCAROWN, AREA, PTRANSIT, POP1990, DENSITY)

The resulting 2SLS model takes the form:

GINI = constant + ***INCOME*** + ***FEMHEAD*** + ***TRANSITC*** + POP1990 + POPGROW + error

The coefficients for ***INCOME*** and ***TRANSITC*** are expected to be negative with the coefficients for ***FEMHEAD*** and POP1990 expected to be positive. A negative sign indicates decreasing levels of income inequality (Gini ratio closer to zero) while a positive sign indicates increasing levels of income inequality (Gini ratio closer to one). It is uncertain whether the variable for population growth rate (POPGROW) should be positive or negative because changes in size are dependent on a range of urban conditions. Rapid population change is also associated with disequalibrium conditions that are likely to include complex social, economic, and environmental disturbances.

The empirical model specified above used MSAs as the unit of analysis. Data for all 285 MSAs were derived primarily from the 1990 census with the exception of transit capacity information (U.S. Bureau of Transportation Statistics), per capita serious crime rates, and employment information (State and Metropolitan Area Data Books). The MSAs included in the analysis represented approximately 75 percent of the 1990 U.S. population.

RESULTS

The equations estimating the proportion of female headed households (***FEMHEAD***), median household income (***INCOME***), and transit capacity (***TRANSITC***) performed relatively well, explaining between 73 and 78 percent of respective variation (see Table 4, 5, and 6). Most of the signs and magnitudes of significant coefficients appear to represent logical relationships. The descriptive statistics for all variables are shown in Table 3. Variables such as population size and median household income were scaled to make interpretation simpler.

The results of the 2SLS model suggest that there is a significant ($p < 0.0005$) and positive relationship between the proportion of female headed households (***FEMHEAD***) and income inequality at the MSA level. This variable was used as an indicator of intervening social, economic, and spatial factors. As was discussed earlier, single-parent households are likely to encounter limited economic and social mobility that results in hardship conditions. For the 1990 MSA data used in this analysis, there were strong positive correlations between percent female headed households and percent on households on welfare ($r = 0.512$) and per capita serious crime rates ($r = 0.418$). There was also a strong negative correlation between percent of female headed households and percent of the MSA population that is white (r = -0.687). It was anticipated that there would be a positive relationship between percent of female headed households and the Gini ratio, along with the variable for household income levels, had a strong influence on predicting income inequality.

Table 3 Descriptive statistics

Description	Mean	Std Dev
Gini concentration ratio based on 1990 income (dependent)	0.354	0.021
Serious crimes reported per capita	57.063	18.849
Geographic size (square miles)	2055.755	2550.485
Population density	292.652	272.065
Full time equivalent workers (weighted by average weeks worked - see Galster 1998)	0.451	0.066
Proportion of female headed households with children	0.154	0.027
Proportion of female headed households with children (predicted)	0.154	0.027
Home price index (percent of mean from all MSAs)	0.683	0.325
Median household income (thousands $)	28.187	4.622
Median household income (predicted)	28.187	4.098
Number of jobs per 100 population aged 15 to 64	0.526	0.163
Male to female ratio (ages 15 to 64)	0.981	0.066
Proportion of persons employed in agriculture	0.026	0.024
Proportion of persons over 25 years with college degree or higher	0.195	0.061
Proportion of persons employed in finance, insurance, or real estate	0.060	0.019
Proportion of population that is male, ages 15 to 64	0.326	0.021
Proportion of persons employed in manufacturing	0.172	0.076
Population in millions	0.684	1.650
Population growth rate from 1970 to 1990	0.336	0.502
Proportion of persons using transit for work commute	0.020	0.025
Proportion of households owning automobiles	0.908	0.029
Proportion of households receiving welfare payments in 1989	0.072	0.027
Proportion of population that is white	0.846	0.108
Rental price index (percent of mean from all MSAs)	0.816	0.160
Transit capacity (directional miles per 100 square miles)	7.070	81.713

Table 4 Regression results for ***TRANSITC***

Variable	B	SE B	Beta	T	Sig T
AREA	-0.02207	0.00153	-0.59223	-14.45500	0.00001
POP1990	58.34605	3.48348	1.01142	16.74900	0.00001
DENSITY	-0.10658	0.01368	-0.30506	-7.79400	0.00001
INCOME	-1.93848	0.77987	-0.09424	-2.48600	0.01350
PCAROWN	-235.39627	144.77253	-0.07293	-1.62600	0.10510
PTRANSIT	717.67429	205.77486	0.19219	3.48800	0.00060
(Constant)	83.94526	20.21070		4.15400	0.00001
Adj. R^2	0.734				
N	282				

Table 5 Regression results for ***INCOME***

Variable	B	SE B	Beta	T	Sig T
EMPPC	-1.90040	3.21605	-0.02726	-0.59100	0.55510
JOBSPC	2.80319	1.02042	0.09869	2.74700	0.00640
FEMHEAD	-19.01741	9.74798	-0.12323	-1.95100	0.05210
PWELFARE	-0.85255	9.43775	-0.00496	-0.09000	0.92810
PAGRI	-11.94856	8.13216	-0.06142	-1.46900	0.14290
PMANUF	16.68782	2.40472	0.27402	6.94000	0.00001
PM15_64	4.69073	11.59807	0.02121	0.40400	0.68620
PWHITE	-0.81694	2.18341	-0.01912	-0.37400	0.70860
PCOLL	10.74954	4.29926	0.14254	2.50000	0.01300
HINDEX	0.30235	0.94452	0.02127	0.32000	0.74910
RINDEX	18.81380	1.95481	0.65217	9.62400	0.00001
POP1990	0.17800	0.09584	0.06356	1.85700	0.06440
PFIRE	33.34242	9.58650	0.13659	3.47800	0.00060
(Constant)	7.37039	4.34297		1.69700	0.09080
Adj. R^2	0.776				
N	281				

Table 6 Regression results for ***FEMHEAD***

Variable	B	SE B	Beta	T	Sig T
EMPPC	-0.02529	0.02875	-0.05599	-0.88000	0.37980
JOBSPC	0.01671	0.00669	0.09080	2.49800	0.01310
PWELFARE	0.58583	0.04777	0.52627	12.26400	0.00001
PAGRI	-0.45092	0.04556	-0.35772	-9.89800	0.00001
PMANUF	0.00521	0.01535	0.01320	0.34000	0.73450
PWHITE	-0.16042	0.01068	-0.57924	-15.01700	0.00001
PCOLL	0.06475	0.02128	0.13251	3.04300	0.00260
HINDEX	-0.02439	0.00606	-0.26478	-4.02500	0.00010
RINDEX	0.01373	0.01298	0.07347	1.05800	0.29110
POP1990	0.00010	0.00061	0.00551	0.16200	0.87110
PFIRE	0.10106	0.05965	0.06389	1.69400	0.09140
MFRATIO	-0.03563	0.02935	-0.07900	-1.21400	0.22580
CRIMEPC	0.00004	0.00006	0.02400	0.65400	0.51350
DENSITY	0.00001	0.00000	0.04887	1.19400	0.23350
(Constant)	0.27877	0.02426		11.49200	0.00001
Adj. R^2	0.789				
N	281				

As expected, the coefficient for household income levels (***INCOME***) was statistically significant ($p < 0.0005$) and had a negative sign. Previous research findings suggest that as average (or median) metropolitan incomes increase, there should be corresponding positive distributional effects. Results from the OLS model suggest that metropolitan areas with more manufacturing, finance, insurance, and real estate related employment have higher average household incomes. Income levels across MSAs also increased as the percent of persons over 25 with college degrees increased. In the 2SLS model, household income levels were more strongly associated with the population size variable compared to the other four variables. It is difficult to interpret the impact of a variable on change in the Gini ratio because the ratio is essentially unitless (see earlier discussion on the Gini ratio). To put the resulting ***INCOME*** coefficient into perspective, the lowest estimated Gini ratio was 0.2989 (Sheboygan, WI) and the highest was 0.4339 (McAllen-Edinburg-Mission, TX), a difference of 0.1350. On average, using the resulting coefficient of –0.00214, it would take an increase of $63,084 per household to create a 0.1350 change in the Gini ratio (with all other variables at the means). While the *average* income level does not capture the structure of the income distribution (i.e., the average household incomes could increase by increasing incomes of those in the top category only), it does give some indication of the magnitude of the ***INCOME*** coefficient.

The coefficient for MSA population size (POP1990), was also statistically significant and had a positive sign. The magnitude of the coefficient is very similar to comparable specifications (see Garofalo and Fogarty 1979; Kennedy and Nord 1984; Chakravorty 1996; Cloutier 1997). These results provide additional support for the theory that urban income inequality increases with population size. The current model also controls for metropolitan characteristics that have been excluded from previous analyses. While the coefficient is positive and significant, the magnitude is relatively small. On average, the increase in the Gini ratio for cities of 100,000 persons versus 1,000,000 persons was 0.002 – which is only 1.48 percent of the difference in ratios between the MSAs for Sheboygan, WI and McAllen-Edinburg-Mission, TX mentioned previously.

Table 7 Regression Results with ***TRANSITC*** (Gini as dependent variable)

Variable	B	SE B	Beta	T	Sig T
FEMHEAD	0.45225	0.03224	0.57358	14.02700	0.00001
INCOME	-0.00214	0.00024	-0.41518	-8.86900	0.00001
TRANSITC	-0.00001	0.00002	-0.02469	-0.41000	0.68180
POP1990	0.00227	0.00089	0.17696	2.55300	0.01120
POPGROW	0.01250	0.00161	0.29710	7.74600	0.00001
(Constant)	0.33894	0.00929	36.46900	0.00000	
Adj. R^2	0.599				
N	281				

Table 8 Regression Results with PTRANSIT (Gini as dependent variable)

Variable	B	SE B	Beta	T	Sig T
FEMHEAD	0.49631	0.03247	0.62945	15.28800	0.00001
INCOME	-0.00156	0.00026	-0.30228	-6.04300	0.00001
PTRANSIT	-0.37046	0.08512	-0.38494	-4.35200	0.00001
POP1990	0.00548	0.00098	0.42813	5.59700	0.00001
POPGROW	0.01041	0.00163	0.24746	6.37900	0.00001
(Constant)	0.32153	0.00953		33.75700	0.00001
Adj. R^2	0.624				
N	281				

The coefficient of most interest to this study was the transit supply. It was hypothesized that increased levels of transit service provision could have income distribution impacts through increasing urban mobility and accessibility – especially for lower income persons. In this case, the transit capacity coefficient was not statistically significant. This means that the 1990 levels of transit service did not appear to be correlated with levels of income inequality (see Table 7). Transit capacity was measured as the number of transit route directional miles per 100 square miles for each MSA. This density measure was used in order to control for MSA size and as an indicator of geographic concentration. Higher transit capacity densities were considered to represent higher levels of service. This is obviously a simplified measure of transit service provision that ignores other factors related to service quality, such as service frequency, reliability, and route connectivity. The measure does not explicitly account for urban rail transit systems that tend to have different ridership characteristics than bus transit. It is likely that the presence of urban rail is implicitly accounted for in the population size variable because the existing urban rail systems are in the largest metropolitan areas. Areas with the lowest transit service densities were MSAs with less than 100,000 persons and the highest were for MSAs having millions of residents. Only eight MSAs provided no formal public transportation service.

When the percent of persons using transit for work trips was substituted for the transit capacity variable (with the same OLS specification in the first stage regression), the coefficient was negative and significant at $p < 0.0005$ (see Table 8). This difference in behavior between the transit capacity and the transit use variables is interesting because ***TRANSITC*** and PTRANSIT were significantly correlated (r = 0.615), leading one to assume that they were representing the dynamic relationship between transit availability and patronage.

On one hand these regression results were not surprising given that MSAs are the unit of analysis. While transit service may be distributed regionally (i.e., extending to suburbs and beyond), most service is concentrated in central cities. The mobility benefits may be diluted at the MSA level because transit plays a significantly smaller role compared to sub-MSA areas such as urban areas or cities. This study does not control, however, for the length of time that transit systems have been in operation in their current configuration. It is possible that mature transit systems more efficiently serve customers because of system responses to actual demand levels. Not controlling for the time lag may not be detrimental to the results of the analysis, however, given the length of time needed to plan and implement transit systems. System user expectations and spatial impacts begin to occur in advance of actual transit operations.

CONCLUSIONS

This analysis represents a re-examination of the relationship between urban income distribution and population size. In addition, the research has focused on two specific aspects; the specification of the regression equation used to predict income inequality and the introduction of a public policy variable into the specification. The research hypothesis tested whether public transportation increases mobility or accessibility and provides benefits that influence the income distribution of metropolitan areas. The results of the 2SLS regression analysis suggest that social and demographic, economic, and spatial characteristics are significant determinants of income inequality. The public policy variable tested, public transportation capacity, was not a significant factor and did not have detectable effects on income distributions across MSAs. On the other hand, the use of public transportation did have a significant correlation with MSA income inequality within the same context.

One explanation for the relative insignificance of transit capacity on metropolitan area income distribution is the fact that only a small percentage of travel at the metropolitan level is by public transit. Only about two percent of all MSA work trips were made by transit in 1990. It is also true that transportation service providers are experiencing substantial difficulties linking residential locations with increasingly dispersed locations (i.e., suburban) of new employment. The results of this analysis could be different if the unit of analysis were central cities instead of metropolitan areas. However, analyzing only central cities may produce misleading income distribution results because central cities, urbanized areas, and suburban rings are linked economically and socially. Further research on the spatial concentration of income and metropolitan fiscal disparities are especially relevant given the continuing economic and social segregation resulting from current development patterns.

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