Income Inequality And Educational Attainment Rates: The New York Story

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ABSTRACT

This paper examines the relationship between changes in income inequality and educational attainment rates in New York counties during the 1990s. The dependent variable is the change in the Gini coefficient over the decade. The independent variables include the Gini coefficient for 1990, educational attainment rates at the high school, bachelor's degree, and graduate/professional levels, the natural logarithm of population density in the county, real public educational expenditures in the county for several years preceding the 1990s, and an index of racial diversity in the county in 1990. Results of OLS regressions suggest that county population density, and educational attainment rates at the bachelor's and graduate degree levels are associated with increases in county income inequality over time. Alternatively, the initial level of income inequality and the high school attainment rate are associated with decreases in income inequality over time in New York counties.

1. INTRODUCTION

From job shortages in the early 1990s to labor shortages later in the decade, the face of New York changed over the last ten years of the 20th century. New York experienced rising income inequality between 1980 and 2000, based on the changes in the Gini coefficient. The Gini coefficient based on household income data for New York was 0.419 in 1980, rose to 0.467 in 1990, and increased to 0.499 in 2000. This represents a 19.1 percent increase over that twenty year period.

Policymakers are often interested in finding ways to mitigate income inequality, but "should an increase in [income] inequality…be considered a favorable rather than an unfavorable development?" (Becker & Murphy 2007). According to Becker and Murphy (2007), "policies designed to deal with inequality must take account of its cause" since in some instances "the rise in inequality [comes] along with an acceleration of economic growth that [raises] the standard of living" (Becker & Murphy 2007). Therefore, this paper is an impartial examination of the factors associated with rising income inequality in an effort to understand its causes in New York counties.

Income inequality arises because citizens differ from one another in characteristics that have an impact on their incomes. According to Weil (2005), these differences across people exist in human capital (i.e., education and health), where they live (e.g., rural vs. urban), their ownership of physical

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capital, their specific skill sets, and their luck (374). The economic climate then translates these differences into differences in income for these individuals. DeFina (2007) cites technological change, immigration, and deunionization as additional contributing factors to income inequality. Becker and Murphy (2007) note that the U.S. has experienced rising income inequality primarily because of educational attainment differences triggered by changes in the returns to education. Thus, we have chosen to concentrate on the role of education in order to see if the recent experience of New York counties with income inequality is consistent with that of the nation.

This paper is organized into six sections: Section 2 presents past research. Section 3 discusses the data and their main characteristics. Section 4 discusses econometric issues and introduces the empirical model. Section 5 presents the empirical findings and section 6 provides a brief conclusion.

2. LITERATURE REVIEW

Schultz (1963) discusses increasing human capital as a way to decrease income inequality; focusing on support for public education as a potential way to decrease it. Ahluwalia (1976), and Papanek and Kyn (1986) suggest that education is associated with equality of income. Conversely, Ram (1989) does not strongly support the idea that increased education will decrease income inequality. It is evident that there is no clear answer as to whether or not investment in education will decrease income inequality over time (Sylwester 2002).

Sylwester (2002 & 2003) conducts two distinct studies using international samples of 50 countries; the first asks if educational expenditures will reduce income inequality, and the second looks at changes in income inequality and enrollment in higher education. Sylwester (2002) concluded that countries that increase the percentage of GDP devoted to education had lower income inequality in subsequent years. Sylwester (2003) could not determine if rising education levels cause the degree of income inequality across countries to converge. However, he does find that countries with larger enrollment rates in higher education saw their income inequality decrease, but only if people could afford not to work and attend school.

Chiswick and Chiswick (1987) explain how increased participation in higher education could change the composition of the labor force. However, they did not determine whether income dispersion would increase or decrease. Chiswick and Chiswick (1987) explain that if few are highly educated, the increased participation in education can temporarily raise income inequality because more individuals from the unskilled cohort move to the skilled cohort. However, over time increased enrollment in education might lower income inequality as more and more unskilled laborers become skilled, which lowers the wage premium for skilled workers (Chiswick & Chiswick 1987).

Alternatively, Jimenez (1986) emphasizes the roles of primary and secondary education in decreasing income inequality and suggests that higher education might actually lead to a more skewed income distribution. Behr et al. (2004) look at income distribution, educational dispersion, and public K-12 educational expenditures at the state-level during the period 1970-2000. They find that a decrease in educational dispersion leads to a decrease in income inequality during the study period. In addition, the results indicate that larger educational expenditures eventually reduce income inequality. Ahluwalia (1976), Marin and Psacharopoulos (1976), Ram (1984), Papanek and Kyn (1986), and Park (1996) all find that greater education levels correlate positively with income equality. However, as previously mentioned, Ram (1989) does not find a strong relationship between education levels and income inequality.

Park (1996) performs a cross-country study of the Kuznets inverted U-hypothesis with an emphasis on the role of education measures. The results indicate that the presence of education variables in the regression weakens the robustness of the Kuznets hypothesis and reduces the income variables' significance. More importantly, however, Park found that education measures alone accounted for 42 percent of the variation in income inequality, as measured by the adjusted R^2.

There have been many studies of income inequality and educational attainment conducted worldwide. However, very few of them have measured income inequality at the sub-unit level (e.g., state or county) of a highly developed economy. Exceptions include Behr et al. (2004), Jenkins and Jozefowicz (2006), and to some extent Sylwester (2002 & 2003). We believe that what is largely true of developing economies, as widely studied in the literature, also holds in certain sub-units of developed economies. Thus, like Jenkins and Jozefowicz (2006), our focus is the county level.

Jenkins and Jozefowicz (2006) study 67 counties across Pennsylvania during the 1990s and observe that an increase in educational attainment rates at the high school and bachelor's degree levels is associated with a reduction in income inequality. The initial level of income inequality in the county also reduces income disparity. Alternatively, they find that population density and educational attainment at the graduate level increase income inequality in a county.

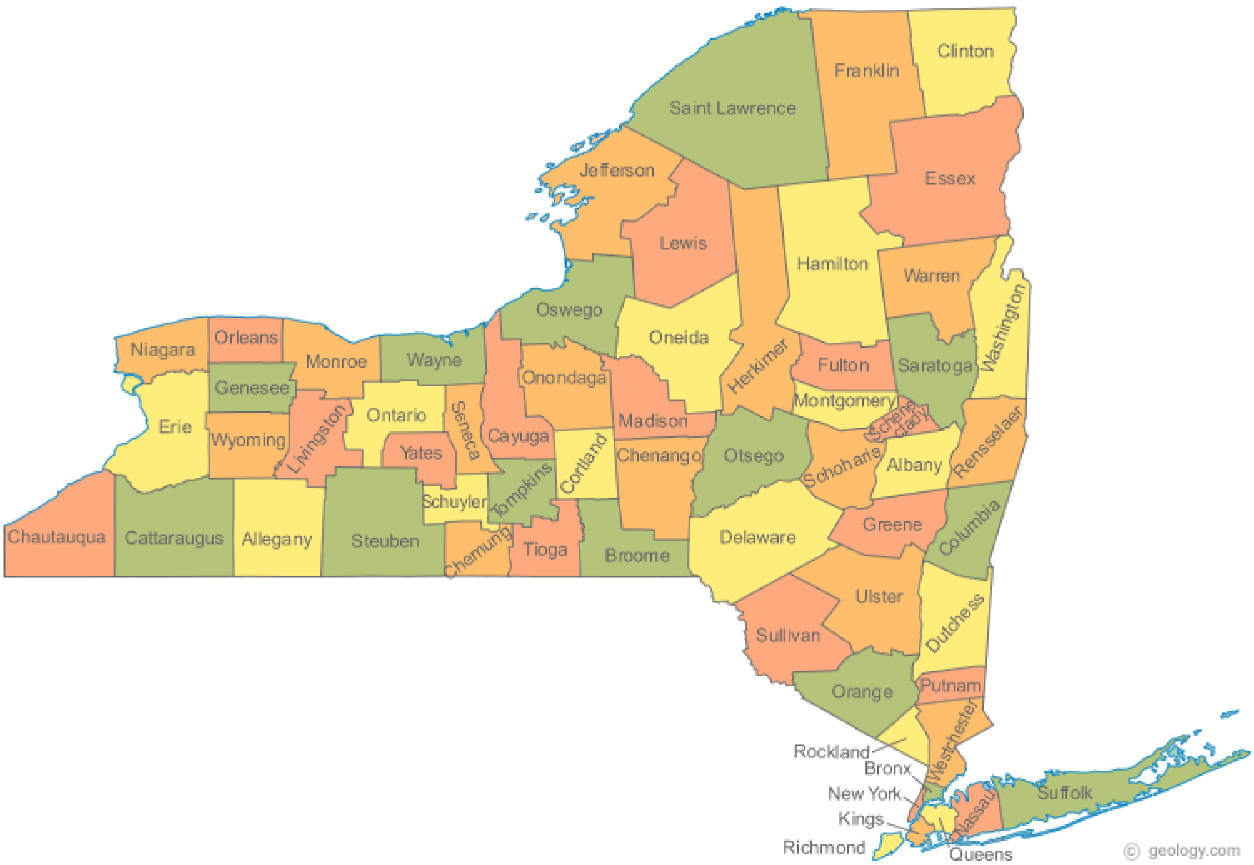
As Jenkins and Jozefowicz (2006) point out, a typical deficiency of cross-country studies is the rather small number of observations in the sample (e.g., Tinbergen (1972) n=3, Psacharopoulos (1977) n=49, Ram (1984) n=28). Another drawback, discussed by Jenkins and Jozefowicz (2006), is that Gini coefficients calculated at the national level mask state differences. In a similar fashion, state-level Gini coefficients mask county differences. Our sample consists of 62 counties in New York, which is large in comparison to many cross-country studies and focuses on the relationship between educational attainment and changes in the Gini coefficient in these counties.

3. DATA

The sample is a cross-section of the 62 counties in New York observed over the period from 1990 to 2000. It is comprised of data from the 1990 and 2000 Census reports, which were retrieved from the U.S. Census Bureau website. For a complete list of the counties please visit http://www.nysac.org/Counties/Member_County_Web_Sites.php . A map of New York State counties can be found in Figure 1.

Figure 1: Map of New York State

Counties



Source: http://geology.com/state-map/new-york.shtml

3.1 Dependent Variable

The change in the Gini coefficient between 1990 and 2000 is utilized as the dependent variable in this study, $\Delta GINI = GINI2000 - GINI1990$. This is consistent with Edwards (1997), Savvides (1998), Sylwester (2002 & 2003), and Jenkins and Jozefowicz (2006). We use the Gini coefficient as a measure of income inequality because of its widespread use in other studies and for comparison purposes. Furthermore, Clarke (1995) finds that the Gini coefficient is correlated with other income inequality measures.

Sylwester (2003) uses a twenty year period (i.e., 1970-1990) when analyzing changes in income inequality, but, like Jenkins and Jozefowicz (2006), this study only considers one decade for the calculation of the dependent variable because the breakdown of income brackets from the 1980 Census was incompatible with that of the 2000 Census for Gini creation. As discussed in Jenkins and Jozefowicz (2006), if the household income data used to formulate the Gini coefficients is not consistent, it would create skewed Gini coefficients. Although a longer time period would be preferred, the availability of appropriate Census data constrains this analysis to ten years.

As mentioned by Jenkins and Jozefowicz (2006) and Sylwester (2002 & 2003), using the change in the Gini coefficient as the dependent variable attempts to reduce reverse causality. Sylwester (2003) suggests, "…it is unlikely that changes in income inequality between periods *s* and *t* should affect…period *s*" (Sylwester 2003, 251). Other studies of the link between educational levels and income distribution, such as Ahluwalia (1976), Slama (1978), Papanek and Kyn (1986), and Ram (1989), have employed a measure of income inequality at one point in time as the dependent variable. However, this may result in reverse causality problems. Is the greater disparity in the educational attainment levels of the population caused by income inequality or do existing differences in educational attainment levels lead to increased income inequality? In contrast, using the current framework, the research question is, do New York counties with higher educational attainment rates at the high school, bachelor's, or graduate levels experience rising or declining levels of income inequality?

3.2 Construction of the Gini Coefficients

The individual Gini coefficients for 1990 and 2000 are calculated as follows:

$$GINI = 1 - \sum_{i=1}^{n} f_i (p_i + p_{i-1})$$

where f_i is the proportion of households in income bracket i and p_i is the proportion of total income received by households in income bracket i and all lower income brackets. The Census uses ten household income brackets (e.g., less than \$10,000; \$10,000 to \$12,999; \$15,000 to \$19,999; etc.).

We assume that each household in an income bracket earns the midpoint of that income range so the total income earned by households in an income bracket is obtained by multiplying the number of households in that bracket by the midpoint. These results are then added up across income brackets to obtain the total income earned by households in a county. The ratio of the total income earned by an income bracket to the total income earned in the county provides the proportion of income earned by households in each income bracket.

The feasibility of approximating the distributions by assigning each household in the income bracket to the midpoint of that bracket for the first nine income ranges (those less than \$200,000) was tested. The estimated aggregate household income for those households earning less than \$200,000 was calculated by multiplying the midpoint of each income bracket by the number of households in that income range and then summing the results. Then, the ratio of the estimated aggregate household income to the actual aggregate household income reported by the Census for those households earning less than \$200,000 was calculated for each county in New York. The majority of the ratios equaled 1.01 with a few 1.02 values. Thus, the validity of using the midpoints of the income brackets is confirmed.

The tenth income bracket published by the Census is $200,000 or more. This presents a problem in the calculation of the Gini coefficient since there is no midpoint for an income bracket that has no finite end. In order to address this difficulty, the average earnings for the $200,000 or more bracket were calculated by dividing the county-specific aggregate household income in that bracket by the number of households in that income bracket in that particular county as reported by the Census. The resulting average earnings for the tenth income bracket were used as its midpoint in the county-level Gini calculations. This approach of creating county-specific midpoints is better than assigning a fixed midpoint for the uppermost bracket to all of the counties in the sample because it yields greater variation in the resulting dependent variable. Since the independent variables are county-specific, it makes sense to have a corresponding county-specific midpoint for the $200,000 or more income bracket.

3.3 Independent Variables and Expected Signs

The independent variables used in this study are the initial level of income inequality, educational attainment rates, the population density, public education expenditures, and an index of racial diversity. This model is similar to both Jenkins and Jozefowicz (2006) and Behr et al. (2004).

The Gini coefficient for 1990 (GINI1990) is the initial level of income inequality in the county. As discussed in Sylwester (2003), it is important to control for potential non-linearities. It is conceivable that counties with more income inequality have rates of educational attainment that differ from those counties with lower income disparity. Sylwester (2003) mentions that observations with Gini coefficients near the extrema of the variable range will be less likely to get closer to those bounds. The expected sign for the GINI1990 coefficient is negative. As noted by Jenkins and Jozefowicz (2006), overall increases in employment levels, like those observed in New York during the late 1990s, may reduce the amount of income inequality.

The educational attainment rates for 1990 are divided into high school graduate or equivalent (HSATT), bachelor's degree (BADEGATT), and graduate degree, which includes doctoral and other professional degrees (GRADATT). Jenkins and Jozefowicz (2006) mention that educational attainment rates serve as proxies for levels of existing human capital at the beginning of the sample period. By calculating these attainment rates separately we can see the individual impact each has on changes in income inequality in New York counties between 1990 and 2000.

The expected sign for HSATT is negative. Based on the work of Jimenez (1986), as the fraction of the population holding a high school diploma increases, *ceteris paribus,* a decrease in income inequality is expected. Jimenez (1986) focused mainly on primary and secondary education in reducing income inequality.

Since college attainment rates are significantly lower than high school attainment rates in New York, it is expected that increasing BADEGATT will increase income inequality. According to Chiswick and Chiswick (1987), the wage premium for college graduates may worsen income equality over time.

GRADATT should raise income inequality. Because fewer people obtain a graduate or higher degree, the wage premium for that educational level is higher, at least initially, as discussed by Chiswick and Chiswick (1987). Clearly, any increases in attainment at the graduate and professional degree levels will contribute to more skewed income distributions, as mentioned by Jenkins and Jozefowicz (2006).

In an effort to control for the extent of urban/rural character of a county, the natural logarithm of its 1990 population density is used as an explanatory variable (LPOPDENS). This is consistent with the approach of Benzing et al. (2003). It is expected that counties with more densely populated areas (i.e., urban areas) will be characterized by increases in income inequality over the decade. Thus, a positive sign is anticipated for this variable.

To control for the racial/ethnic composition of a county, an index of racial diversity (RACE90) is included. RACE90 is based on Alesina et al. (1999), and it is calculated as follows:

$$RACE90 = 1 - \sum_i (Race_i)^2$$

where $Race_i$ represents the share of population self-identified as $i =$ (White, Black, Asian and Pacific Islander, American Indian, and Other). This variable measures the probability that two people randomly selected from a county will belong to different racial/ethnic groups. It is anticipated that RACE90 will have an ambiguous impact on the dependent variable.

Total real expenditures for public education (TOTEDEXP) within a county for the years 1962, 1977, and 1982 are included to reflect the allocation of resources to public education. Fields (1980), Jimenez (1986), Sylwester (2002), and Behr et al. (2004) have studied the role of public education expenditures in affecting the income distribution. Since it takes time for spending on education to affect income inequality, the sum of the lagged education expenditures is employed to smooth out fluctuations and more accurately represent the effect of education spending on the stock of human capital. While a longer consecutive time series of such expenditures would be desirable, data availability issues constrain it to just the three years mentioned, and data were unavailable for the five New York City counties. Sylwester (2002) uses ten years in his study because of similar data availability issues. As discussed by Behr et al. (2004) and De Gregorio and Lee (2002), we hypothesize that more money devoted to public education will reduce income inequality over time. Therefore, TOTEDEXP should have a negative impact on the dependent variable.

3.4 Descriptive Statistics

Descriptive statistics appear in Table 1. The mean of the county Gini coefficient rose 0.023135 over the ten year period from 0.420335 in 1990 to 0.457413 in 2000. The median Gini coefficient rose from 0.414 in Madison County to 0.458 in Rensselaer County in 2000. The maximum Gini in 1990 was 0.583 in New York County and 0.609 in New York County for 2000. The average change in the county Gini coefficient from 1990 to 2000 was 0.037078 with a standard deviation of 0.028105.

Table 1: Descriptive Statistics

VARIABLE	MEAN	ST.DEV	MAX	MIN
∆Gini	0.037078	0.028105	0.067272	-0.108138
Gini1990	0.420335	0.031944	0.583414	0.366794
HSATT	34.28856	4.826807	44.84964	15.88746
BADEGATT	10.67092	3.625878	22.12967	5.891397
GRADATT	7.705389	3.688004	23.47682	3.642311
RACE90	0.143436	0.148855	0.675181	0.011694
TOTEDEXP	4.80×10^8	8.52×10^8	4.30×10^9	16206737
LPOPDENS	5.334915	1.85904	10.86703	1.131402

The averages for the 1990 educational attainment variables are 34.28 percent for high school, 10.6 percent for bachelor's degree, and 7.70 percent for graduate degree or higher. The maximum high school attainment rate was 44.84 percent in Livingston County, while the minimum high school attainment level was 15.87 percent in New York County. The highest level of bachelor's degree holders was 22.12 percent in New York County, and the lowest was 5.89 percent in Lewis County. The highest level of graduate degree holders was 23.47 percent in Tompkins County, followed by New York County where 20 percent of the population held graduate degrees.

Mean population density in 1990 was 2,537 people per square mile. Maximum density was 52,419 people per square mile in New York County, while minimum was a mere 3.1 people per square mile in Hamilton County.

4. MODEL

4.1 Econometric Issues

The educational attainment rate variables (HSATT, BADEGATT, and GRADATT) are highly correlated with one another. Therefore, in order to avoid multicollinearity problems, only one educational attainment rate will be included at a time. Preliminary regressions were run using only two or all three educational attainment rates together, but multicollinearity was clearly evident.

In addition, there is concern that the New York City counties (i.e., Bronx, Kings, New York, Queens, and Richmond) are outliers in the sample. Therefore, regressions are run on both the full sample (n = 62) and a sub-sample, which excludes the New York City counties (n = 57).

Finally, the expectation that the stochastic error term will have a constant variance across observations is confirmed by the results of White tests for heteroskedasticity in some models, but not in others. As a result, where necessary, the standard errors are corrected using the White heteroskedasticity-consistent variance-covariance matrix.

4.2 Regression Models

Four different model specifications are estimated. The models vary by the number of counties used (i.e., full sample or sub-sample which omits New York City counties), whether RACE and/or TOTEDEXP are included, and by the choice of educational attainment variable (e.g., HSATT, BADEGATT, or GRADATT) used. The lack of available data for TOTEDEXP for New York City counties limits the number of regression models for the full sample. The models are summarized as follows:

$$\Delta GINI = \beta_0 + \beta_1(GINI1990) + \beta_2(LPOPDENS) + \beta_3(EDATT) + \varepsilon \quad \textbf{(1)}$$

$$\Delta GINI = \beta_0 + \beta_1(GINI1990) + \beta_2(LPOPDENS) + \beta_3(EDATT) + \beta_4(RACE90) + \varepsilon \quad \textbf{(2)}$$

$$\Delta GINI = \beta_0 + \beta_1(GINI1990) + \beta_2(LPOPDENS) + \beta_3(EDATT) + \beta_4(TOTEDEXP) + \varepsilon \quad \textbf{(3)}$$

$$\Delta GINI = \beta_0 + \beta_1(GINI1990) + \beta_2(LPOPDENS) + \beta_3(EDATT) + \beta_4(RACE90) + \beta_5(TOTEDEXP) + \varepsilon \quad \textbf{(4)}$$

5. RESULTS

5.1 Full Sample Findings

The results presented for Model 1 appear in Columns 1-3 of Table 2 and are based on the full sample. In Column 1, GINI1990, LPOPDENS, and HSATT show expected signs, but only GINI1990 is statistically significant. The negative and statistically significant estimated coefficient for GINI1990 indicates that high-income inequality counties are more apt to experience a decline in their income inequality over time. Jenkins and Jozefowicz (2006), Sylwester (2003), and Benabou (1996) obtain similar results. In addition, the high school attainment rate is associated with less income disparity over the decade, while greater population density leads to greater income inequality. Jimenez (1986) also finds that secondary educational attainment leads to reduced income inequality.

The results presented in Column 2 replace HSATT with BADEGATT. In this regression, both GINI1990 and LPOPDENS are statistically significant with the expected signs. Although BADEGATT is not statistically significant, it appears that increasing bachelor’s degree attainment rates leads to an increase in income inequality over time. A positive and significant coefficient on LPOPDENS was also obtained by Jenkins and Jozefowicz (2006).

Table 2: Ordinary Least Squares Regression Results
(Full Sample)

Dependent Variable: $\Delta GINI$

	MODEL 1			MODEL 2		
Independent Variable	**Column 1**	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**
Constant	0.2344 (2.714)	0.1205 (2.400)	0.1441 (2.807)	0.2077 (2.240)	0.1075 (1.726)	0.1309 (2.017)
GINI1990	-0.3725** (-2.554)	-0.2943** (-2.180)	-0.3529** (-2.522)	-0.3244** (-2.054)	-0.2694* (-1.765)	-0.3275** (-2.050)
LPOPDENS	0.0037 (1.365)	0.0045* (1.768)	0.0050** (2.117)	0.0061 (1.512)	0.0058 (1.301)	0.0061 (1.494)
HSATT	-0.0017 (-1.593)			-0.0017 (-1.600)		
BADEGATT		0.0014 (1.294)			0.0013 (1.085)	
GRADATT			0.0018* (1.707)			0.0017 (1.539)
RACE90				-0.0423 (-0.808)	-0.0201 (-0.357)	-0.0184 (-0.338)
Adjusted R^2	0.101	0.088	0.151	0.096	0.074	0.093
N	62	62	62	62	62	62

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
Note: The t-statistics appear in parentheses below the estimated coefficients.

In Column 3 in Table 2, GRADATT is used in place of HSATT and BADEGATT. In this case, all three variables are statistically significant with the expected signs. Educational attainment at the graduate/professional level is associated with an increase in income inequality during the 1990s in New York counties. In their analysis of Pennsylvania counties, Jenkins and Jozefowicz (2006) also found a positive sign on GRADATT.

The findings obtained after adding RACE90 as an independent variable in Model 2 appear in Columns 4-6 of Table 2. In Column 4, the results are unchanged in terms of signs and significance. The same is true in Column 5, except LPOPDENS becomes insignificant. In the case of Column 6, both LPOPDENS and GRADATT lose their statistical significance. RACE90 is not statistically significant in any model, but it carries a negative sign throughout. This suggests that greater racial diversity in a county fosters reductions in income disparity over time.

5.2 Sub-sample Findings

In Table 3, the results are based on the sub-sample, which excludes the five New York City counties, and Model 1 appears in Columns 1-3. The findings in Column 1 reveal expected signs for GINI1990, LPOPDENS, and HSATT, and statistically significant coefficients for GINI1990 and HSATT. This is in contrast to the full sample results in Table 2, where HSATT was not significant, but still retained a negative sign. The findings for Column 2 are similar to Column 1 in that GINI1990 and the educational attainment variable are significant. However, in this regression, BADEGATT is used as the measure of educational attainment, and it has a positive sign. In Column 3, GINI1990 and GRADATT are both significant. GINI1990 continues to have a negative sign, while GRADATT has a positive coefficient. These signs are consistent with Jenkins and Jozefowicz (2006). LPOPDENS is not statistically significant in any of these models, but it maintains a positive sign.

Table 3: Ordinary Least Squares Regression Results
(Sample excluding New York City Counties)

Dependent Variable: $\Delta GINI$

	MODEL 1			MODEL 2		
Independent Variable	**Column 1**	**Column 2**	**Column 3[a]**	**Column 4**	**Column 5**	**Column 6[a]**
Constant	0.2969 (2.637)	0.1608 (2.1752)	0.2062 (1.901)	0.2837 (2.569)	0.1186 (1.462)	0.1632 (1.704)
GINI1990	-0.4522** (-2.306)	-0.3817** (-2.058)	-0.4890* (-1.943)	-0.3638* (-1.838)	-0.2997 (-1.528)	-0.4069* (-1.817)
LPOPDENS	0.0014 (0.360)	0.0004 (0.107)	0.0019 (0.382)	0.0053 (1.193)	0.0037 (0.755)	0.0055 (1.039)
HSATT	-0.0023* (-1.791)			-0.003** (-2.328)		
BADEGATT		0.0029* (1.916)			0.0031** (2.002)	
GRADATT			0.0030* (1.934)			0.0032* (1.940)
RACE90				-0.1360* (-1.822)	-0.0880 (-1.231)	-0.0964 (-1.294)
Adjusted R^2	0.094	0.102	0.123	0.132	0.110	0.137
N	57	57	57	57	57	57

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
[a] Standard errors are White heteroskedasticity-consistent.
Note: The t-statistics appear in parentheses below the estimated coefficients.

By omitting the New York City counties, the signs on the coefficients in Table 3 are unchanged from Table 2, but there are increases in significance for the HSATT and BADEGATT educational attainment variables. LPOPDENS loses what significance it had once the New York City counties are removed in Table 3.

In Model 2, RACE90 is added as an independent variable in Columns 4-6 of Table 3. In Column 4, the results are robust in sign across the board. GINI1990 loses some significance and becomes insignificant in Column 5. In all three columns, RACE90 retains its negative sign, but it is only statistically different from zero in Column 4 in the presence of HSATT.

Real total expenditures on public education in the county for the years 1962, 1977, and 1982 are added in Model 3, which appears in Columns 1-3 of Table 4. In Column 1, the signs on the estimated coefficients are unchanged. The significance levels of the existing variables remain largely the same, but HSATT increases in significance in Column 1 and GINI1990 loses some significance in Column 2. While the estimate on the education expenditures variable is not statistically significant, it does have the expected negative sign indicating that higher spending on public education will lead to less income inequality over time. Jenkins and Jozefowicz (2006) and Behr et al. (2004) also find that educational expenditures reduce income inequality.

Table 4: Ordinary Least Squares Regression Results
(Sample excluding New York City Counties)

Dependent Variable: $\Delta GINI$

	MODEL 3			MODEL 4		
Independent Variable	**Column 1[a]**	**Column 2[a]**	**Column 3[a]**	**Column 4[a]**	**Column 5[a]**	**Column 6[a]**
Constant	0.2584 (2.107)	0.1331 (1.678)	0.1783 (1.847)	0.2581 (2.059)	0.1007 (1.376)	0.1451 (1.670)
GINI1990	-0.4167** (-2.007)	-0.3533* (-1.765)	-0.4583* (-1.922)	-0.3478* (-1.768)	-0.2874 (-1.594)	-0.3917* (-1.781)
LPOPDENS	0.0054 (0.910)	0.0046 (0.847)	0.0059 (1.239)	0.0077 (1.231)	0.0069 (1.129)	0.0085 (1.500)
HSATT	-0.0021** (-2.019)			-0.0029** (-2.454)		
BADEGATT		0.0030* (1.938)			0.0031* (1.906)	
GRADATT			0.0030* (1.857)			0.0032* (1.871)
RACE90				-0.1225 (-1.616)	-0.0743 (-1.075)	-0.0832 (-1.194)
TOTEDEXP	-7.36×10^{-12} (-1.092)	-8.66×10^{-12} (-1.288)	-8.29×10^{-12} (-1.331)	-5.15×10^{-12} (-0.899)	-7.66×10^{-12} (-1.244)	-7.15×10^{-12} (-1.281)
Adjusted R^2	0.101	0.118	0.137	0.127	0.119	0.169
N	57	57	57	57	57	57

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.
[a] Standard errors are White heteroskedasticity-consistent.
Note: The t-statistics appear in parentheses below the estimated coefficients.

We suspect that the lack of statistical significance for the educational expenditures variable has more to do with data limitations than its lack of relevance to the study. In particular, only three years of data were available to construct this variable while other studies have used much longer consecutive time series to measure similar effects. As pointed out by Sylwester (2002), improvements in income inequality due to educational expenditures occur only very slowly, and three years is probably not enough time for such effects to become evident.

Columns 4-6 in Table 4 represent Model 4 and include both RACE90 and TOTEDEXP. In all cases, the signs of the variables remain the same and the significance levels are roughly consistent with previous findings. GINI1990 loses some significance in Column 4 and becomes insignificant in Column 5. RACE90 and TOTEDEXP exhibit the negative signs that they have in other models when analyzed separately, but neither variable is statistically significant. RACE90 was significant at the 10 percent level in Column 4 of Table 3 and barely misses that level of significance in Column 4 of Table 4.

There is an issue concerning whether TOTEDEXP is capturing a quantity or a quality effect of education on income inequality. In an effort to address this concern, the 1990 enrollment rates for primary/secondary school and college from the Census were included in Models 3 and 4. The addition of these variables has no impact on the signs of the original independent variables and little to no effect on the significance levels of these variables. In the case of Model 3, neither of the enrollment rate variables is statistically different from zero. In the case of Model 4, only the college enrollment rate variable is significant at the 10 percent level. TOTEDEXP remains insignificant throughout these regressions. Sylwester (2002) points out that the educational expenditure variable will have an impact on income inequality changes independent of enrollment rates (as a measure of the quantity dimension) if the educational expenditures are improving educational quality, which is affecting income inequality. Based on these findings, the quantity aspect receives some support because only the college enrollment rate is significant and only in some of the regressions.[2]

5.3 Summary of Findings

Overall, GINI1990 has a negative and statistically significant estimated coefficient in all but two regressions. The sign for this variable agrees with expectations and the findings of Jenkins and Jozefowicz (2006), Benabou (1996), and Sylwester (2003).

Although the significance of the educational attainment variables is not consistent across the samples, their signs are remarkably robust. These findings suggest that increases in educational attainment rates at the high school level in New York counties, *ceteris paribus*, result in reductions in income inequality over time. However, the opposite is true at the college and graduate education levels. As noted by Chiswick and Chiswick (1987), this may suggest that the wage premium for workers with bachelor’s degrees or graduate degrees had not yet declined appreciably in New York counties during the 1990s.

6. CONCLUSIONS

The signs of the estimated coefficients in the analysis are robust. It appears that the initial level of income inequality and high school attainment rates in a county are both associated with decreases in income inequality during the 1990s for New York. Policymakers seeking to understand the behavior of income inequality within the state of New York will find these results of interest.

The importance of educational attainment rates in reducing income inequality in New York counties demonstrated by the findings of this study supports the findings of other researchers. While Ram (1989) concludes that there is not strong support for the notion that increasing education leads to less income inequality, studies by Ahluwalia (1976) and Papanek and Kyn (1986) find that educational achievement promotes income equality. More specifically, the negative sign on HSATT and the positive signs on BADEGATT and GRADATT confirm the suggestion by Jimenez (1986) that educational attainment at the secondary school level will reduce income disparity while higher educational attainment will yield more skewed income distributions.

6.1 Future Research

Educational attainment rates at various levels are not accidental. Decomposing the reasons behind them was beyond the scope of this study, but the significance of educational attainment rates in explaining income inequality demonstrated by this analysis indicate that further investigation is warranted.

Another issue outside the purview of this study, but worthy of further inquiry is the extent to which in-migration and out-migration of educated individuals across New York counties occurs. Clearly, the movements of these individuals will affect the educational attainment rates measured within counties by the Census and provide a reflection of the economic base of the counties.

ENDNOTES

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2. These regression results are available from the authors upon request.

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