Income Inequality, Incarceration, and Black-White Poverty Rate Differentials

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Abstract
This paper attempts to analyze and isolate the effects of income inequality on the difference between poverty rates amongst the Black and White population by state in 2010, using each state's GINI coefficient estimate as the inequality measurement. In addition, the author proposes an alternative income distribution measurement to try and further interpret the effects of a particular state's income allocation on its poverty rate differential. This paper will also discuss, and attempt to quantify, other factors that could affect disparity in poverty rates between Black and White Americans, such as incarceration rates. The author finds that there is some evidence that a higher state GINI coefficient corresponded with a smaller magnitude of difference between Black and White poverty rates, while a higher variance in allocation amongst income brackets corresponded with an increase in the magnitude of the poverty rate differential.
Inequality, Incarceration, and Black-White Poverty Rate Differentials

Connor B. Stanhope

Introduction

The motivation behind this paper comes from the increasing prevalence of the debate in the United States surrounding the equity of the current income distribution, and whether or not our current economy is structured in a way that alienates the poor. A subset of this conversation is that not only are there an increasing number of people that believe our current income inequality is disproportionately burdening the less fortunate, but many also believe that this growing inequality negatively impacts Black Americans by furthering the socioeconomic divide between races. The primary research question is whether or not an increase in income inequality has a larger impact on Black poverty rates than White poverty rates, analyzed by their movement together.

A secondary research question, and one of sociological interest, is to determine the impact between incarceration rates and the Black-White poverty rate differential. Although it is well documented that an increase in income inequality generally causes an increase in the poverty rate, the particular magnitude of its effect on poverty by race is neither intuitive nor documented. Similarly, the particular effect of incarceration rates on the difference between the poverty rates of Black and White Americans is not documented, despite the knowledge that states with higher incarceration rates may generally be states with higher levels of poverty.

In addition, this paper proposes a theoretically optimal distribution of income, and develops a numerical quantification for the distance a society is from that position of theoretical optimality. This paper uses data obtained from the 2010 US Census Bureau, as well as supplementary data from the US Bureau of Justice Statistics, the Bureau of Economic Affairs, and the Council for Community and Economic Research. The paper proceeds as follows; Section 1 will give a brief overview of the existing and relevant literature surrounding this topic, Section 2 discusses and describes the characteristics of the obtained data, including an explanation of the calculations behind relevant independent variables, Section 3 outlines the methodology used as well as the proposed models, Section 4 discusses the results, and Section 5 discusses the author’s conclusions.

Brief Overview of Existing Literature

While literature covering the precise topic of this paper does not exist, there are several academic studies that have been done that provide relevant background information. In a paper written by Bruce Western of Princeton University and Becky Pettit of Washington University entitled “Black-White Wage Inequality, Employment Rates and Incarceration” the authors aim to examine an adjusted measurement of relative Black-White wage inequality by accounting for labor inactivity. This adjusted measurement incorporates incarceration rates of Black men compared to White men, in order to analyze the difference in wages of Black and White men over a period of twenty years, under the scenario that both demographics had the same level of labor activity. The study finds that the real wage gap between Black and White men is inflated by levels of labor inactivity amongst black men, due to their high level of incarceration rates. This particular paper is pertinent to the author of
this paper’s eventual conclusions about incarceration rates and its effect on poverty. In a chapter in the book *Handbook of Income Distribution* entitled “Empirical Evidence on Income Inequality in Industrialized Countries,” authors Peter Gottschlack and Timothy M. Smeeding analyze data of income inequality amongst industrialized countries and observe that there is in fact a positive relationship between income inequality and poverty rates, and also find that income inequality has almost universally risen over that past decade. In a chapter of his book *Economic Inequality and Poverty*, author Stephen Jenkins denotes the distinction between ordinal inequality and cardinal inequality. Jenkins analyzes the concept of cardinal utility through the lens of a hypothetical social welfare function, and provides an analysis of an ideal cardinal inequality distribution similar to the one hypothesized by this paper’s author in a forthcoming section.

**Explanation of the GINI Coefficient**

Developed in 1912 by an Italian statistician, the GINI Coefficient is essentially a measurement of the distance a particular population’s income distribution is from perfect equality, i.e. every single person having the same amount of money. A population’s income distribution, known as the Lorenz Curve, is measured using cumulative share of income as a function of the cumulative percentage of households from lowest to highest income. For example, a population with a perfectly equal income distribution has a Lorenz curve equal to y=x, since every one percent increase in percent of households corresponds with a one percent increase in the total share of income. The actual calculation of the GINI coefficient compares the population’s Lorenz curve with this line of equality, by calculating the ratio of the area of the region between the line of equality and the actual distribution, to the total area underneath the line of equality. Denoting the area underneath the Lorenz Curve as \( B \) and the area between the Lorenz curve and the line of equality as \( A \), then \( G = A/(A+B) \). Since both the X and Y axes only take on values from 0 to 1 (0 to 100 percent), the area \( A+B \) must be equal to one half\(^1\) and thus \( G = 2A \). Since \( A+B = .5 \), \( A = .5-B \) and \( G = 1-2B \). The region \( B \) is the area underneath the Lorenz curve, and thus the formalized equation for the GINI coefficient is

\[ G = 1-2\int_0^1 L(x) \, dx \]

**Summary of Data Collected**

All data collected is for the year 2010, for each individual state. The author uses the 2010 Census to collect data on the GINI coefficient, poverty rates for both Black and White residents, unemployment rates for both Black and White residents, levels of education amongst the Black and White population (percentage of people with a bachelor’s degree or higher), incarceration rates from the Bureau of Justice Statistics, GDP per capita from the Bureau of Economic Affairs (“domestic” meaning “by state” in this context), and the Cost of Living Index from an independent website. Values of the state GINI Coefficient range from .419 (Utah) to .532 (District of Columbia), with an average of approximately .454. The highest level of Black poverty rates in 2010 was seen in Maine, where 42.64% of Black residents lived in poverty. It should be noted however that the Black population of Maine is only 1.3% of the entire population (slightly over 17,000 people). The lowest rate of Black

\(^1\) Region \( A+B \) forms a triangle, thus its area is \( 12 bh \) where both \( b \) and \( h \) are equal to one
poverty was 9.68% in Hawaii, with a nationwide average of 26.21%. The highest level of White poverty occurred in West Virginia, at 16.75%, the lowest rate occurring in Alaska at 6.49%, with a nationwide average of approximately 10.82%. The Cost of Living Index (COL), has a similar calculation to the Consumer Price Index (CPI), in the sense that is an index number with a base 100, where the total cost of living in a particular state is compared to the base. In other words, a state with a COL of 95 has a cost of living that is 5% less than the base region (Montana). The highest COL in the United States in 2010 was 165.56 (Hawaii), the lowest was 89.21 (Kentucky), with an average of approximately 104.65. The author also uses data from the US Census to analyze the distribution of incomes of the Black and White population into each income bracket stipulated by the census, to attempt to develop an alternative income inequality measurement that the author will refer to as the “distribution variance.”

Calculation of the Distribution Variance

The idea of the distribution variance is motivated by the fact that the GINI coefficient as an income inequality measurement compares the existing income distribution to perfect income equality, i.e. the scenario in which every single person within a population has the same amount of money. This type of income distribution is quite obviously unrealistic, and is also undesirable. A functioning economy needs the lure of increased monetary gain to incentivize innovation and development. However, there is evidence to suggest that an income distribution skewed towards the wealthy can cause a macroeconomic production deadweight loss, since the allocation of individuals into each particular income bracket does not always correspond with those that necessarily provide an equivalent amount of value towards the economy. The current environment of a low level of socioeconomic class mobility would tend to indicate that increasing income inequality would continue to limit the contributions of potentially innovative individuals that reside in lower income brackets, since they would not have been given the opportunity, nor the monetary reward, to exhibit their particular talents. The ideal society, however utopic, is one in which each person can be precisely rewarded for the level of contribution they provide, with the presence of perfectly frictionless class mobility if one’s contribution was to increase. In this way, income inequality would still exist, yet disproportionate class inequality would not. Since it is relatively impossible to provide ubiquitously perfect compensation across an entire society, i.e. to universally provide wages that exactly equal the marginal product of labor of an individual, theoretically a society could be divided into “classes” (income brackets), that would contain a range of compensatory values that are roughly equivalent to the range of true marginal products of labor for the individuals in a given bracket. In other words, instead of perfectly assigning compensation to a specific individual based on their specific marginal product, this utopic society would assign compensatory ranges corresponding to an equivalent range of marginal products such that each class, or income bracket, would contain the same number of individuals. The idea of the “distribution variance” is the idea of a calculation for how much a particular population varies from this theoretically perfectly equitable income distribution. In

\[2\] A table of summary statistics on all relevant variables can be found in Table 1 on page 10

\[3\] The author defines a “perfectly equitable income distribution” as a distribution in which each
the United States, the census calculates the number of households (both for the entire population and by ethnic group) that are within each stipulated income group. The defined income groups are for entire households (of any number of members) for a given year, and are divided into 16 brackets. Interpreting each one of these 16 income brackets as class definitions, a perfectly equitable distribution would contain 6.25% of the entire population within each income bracket. The calculation of the distribution variance would be the total population variance amongst income brackets from 6.25%.

Each point on the x axis represents a different income bracket, and its corresponding y value is the percentage of the population within that particular income bracket. The line running through the middle of the graph is the line representing the perfectly equitable distribution.

In other words, the calculation is how much the actual allocation of people into income brackets varies from the perfectly equal allocation of 6.25% in each bracket. The formula for the distribution variance is simply the population variance formula, \( \mu = 6.25 \) and 15 degrees of freedom. The obvious limitation of this calculation is that mobility between income brackets is frictioned by more than just a “marginal product,” meaning that a lower distribution variance would not necessarily imply a more functioning society since individuals are not necessarily in the appropriate income bracket that corresponds to their contribution to society. However, the author does find some evidence (to the 1% significance level) that, after controlling for other factors, an increase in the distribution variance did in fact have a negative impact on GDP in 2010. However, an analysis of the impact of this variance on poverty rates may present a limitation, or a possible multicollinearity, in the sense that some of the poverty rate is directly explained in the calculation of the distribution variance. The Federal government defines different poverty rates depending on the number of members per household, however the data that the author collects for income is data that is calculated as a household total, with no specification of the number of members. Therefore, the calculation of the distribution variance is the calculation of the variance in the percentages of households within a particular income bracket from the perfectly equitable income bracket allocation. This means that some of the households in a handful of the lower income brackets would be below the poverty rate. For example, a single mother of 4 that makes $30,000 a year would be considered to be below the poverty line, yet a person living on their own making $30,000 dollars a year would be well above the poverty line. This means that some of the variability in the poverty rate is directly explained within this distribution variance variable, which could cause some problems in the interpretation of

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4. The 16 income brackets must total to 100% of the population, therefore if each one contained the same number they would have (100/16)% of people, which is equal to 6.25%

5. A brief explanation of the methodology and the results behind this claim are available on page 10
the validity of the results. This will be referenced again in both the methodology and results sections.
Model 1 Specification

The first model the author estimates is to observe the impacts of the GINI coefficient on the Black-White poverty rate differentials. The proposed general OLS model is the difference in poverty rates between the Black and White population by state, as a function of the natural log of the GDP per capita by state, the difference in the percentage of the Black and White population with a bachelor’s degree or higher, the natural log of a state’s incarceration rate per 100,000 people, the cost of living index for each state, and the GINI coefficient for each state. With the GINI coefficient being a ratio, the author argues it may not be valid to take the natural log of this number. The author also includes a vector of indicator controls for region (Central, Pacific, Western and Southern, with Northern as the reference group). The model will be estimated with robust standard errors, due to the likely presence of heteroscedasticity. β_1 is expected to be positive, since an increase in the difference of unemployment rates between Black and White people would most likely increase the difference in the poverty rates of the two races. β_2 is expected to be negative, but possibly not significant, since an increase in the GDP per capita would most likely decrease the poverty rates of both Black and White Americans, and therefore its effect on the difference in poverty rates may be ambiguous. β_3 will most likely be positive, since an increase in the disparity between the number of members of the White population with bachelor’s degrees or higher and number of members of the Black population with Bachelor’s degrees or higher will most likely increase the difference in poverty rates amongst the Black and White population. β_4 is expected to be positive, since a higher incarceration rate would probably indicate a higher poverty rate overall, and probably have an effect of larger magnitude for Black poverty rates, thus increasing the differential. β_5 is expected to be negative, since a higher cost of living would most likely disproportionately increase Black poverty rates as opposed to White poverty rates. The expected sign of β_6 is not intuitive, but the author hypothesizes that it may be positive. This would be due to the skewed level of income inequality towards the Black population. In other words, since the White population earns substantially more, on average, than the Black population, an increase in overall income inequality may imply an increase in this wage gap, thus likely increasing the poverty rate differential.

Potential Limitations of Model 1

The most glaringly obvious limitation of the model is the immeasurability of several factors that may impact the difference between White and Black poverty rates. The main immeasurable variable in this particular regression is the potential levels of discrimination between the Black and White populations. This discrimination factor could manifest itself in the poverty rate differential since it may affect the types of jobs Black people get compared to White people, or just the opportunities that they receive in general. The unemployment rate differential and educational differential variables serve as proxy variables for some elements of discrimination, but its entire impact on poverty rates is at least partially

\[ H_0: \beta_6 = 0 \]
\[ H_A: \beta_6 \neq 0 \]
immeasurable. An additional but related limitation is the potential omitted variable bias present due to the inability to control for all the factors that affect the poverty rates, regardless of their measurability. The small sample size of the data limits the number of controls that can be appropriately added to the model, so as to avoid over-specification. An aforementioned limitation is the gaps in census data estimates. The census does not calculate data for all of the variables for every state, and therefore the proposed model will have observational gaps. As previously stated, the data is likely to be heteroscedastic, however, since the variance in the conditional errors will most likely not be able to be measured by any type of multiplicative constant, nor with any type of functional pattern, a robust standard error estimation should most likely account for the present heteroscedasticity. The final limitation for model 1 that the author acknowledges is that the calculation of the GINI coefficient assumes normality within each granulated segment. Since an accurate estimation of the precise cumulative share of income for each one percent division of a population is relatively impractical, the US census divides the calculation into granulated segments. However, one can imagine a scenario in which a small number of households within the top 5% of overall income earners hold a large cumulative share of income. This would bias the estimate of the GINI coefficient, since the top 5% of income earners would have a disproportionately large share of the overall income that may not be representative of the actual inequality of the population income distribution. The same concept can apply to the lowest 5% of households, where a small amount of households hold a very small share of the aggregate income.

**Model 2 Specification**

The author specifies the second model to attempt to analyze the effects of the previously described distribution variance on the Black-White poverty rate differentials, using the same independent variables, replacing the GINI coefficient variable with the natural log of the distribution variance variable. The value of this coefficient is once again not intuitive, however the author hypothesizes that the relationship will also be positive, since an increase in the variance from a perfectly equitable distribution would imply larger clusters of people in specific income brackets, and, since Black Americans tend to have higher poverty rates, the Black population may have higher clusters of populations in the lower income brackets, thus resulting in a higher distribution variance, and increasing Black poverty rates by more than White poverty rates. Model 2 is also expected to exhibit properties of heteroscedasticity, and therefore will be estimated using robust standard errors. As with the first model, the particular form of heteroscedasticity is most likely not patterned, and therefore simply using robust standard errors will most likely be an appropriate correction for this potential limitation.

**Limitations of Model 2**

The limitations described for model 1 will also be present (minus the issue related to the GINI coefficient). Additionally, there is a potential collinearity problem between the distribution variance variable and the

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7 The value of these particular granulations is not made apparent, but the author postulates that is most likely to 5% segments, based on information from World Bank calculations of global GINI coefficients.
poverty rate differential variable, as described previously. However, it may still be interesting to analyze the overall effect of the overall distribution variance on the difference between Black-White poverty rates, since the poverty rate measurements are divided by race, and the distribution variance is calculated for the total population. Because of this difference, the author argues that this potential collinearity problem will not invalidate the model.

Results for Model 1

A regression of the previously specified format on the observed data results in the following observations. The unemployment differential, educational differential, \( \ln(\text{Incarceration}) \) and cost of living index variables are all statistically significant at the 5% level, with the GINI coefficient variable significant at the 10% level. The unemployment differential yielded a positive effect on the poverty rate differential, as expected, with every one point increase in the unemployment rate differential corresponding to approximately a .485 point increase in the poverty rate differential. The educational differential coefficient also exhibited a positive impact on the poverty rate differential, which was also expected, with a one point increase in the education difference corresponding with a .577 point increase in the poverty rate differential. The incarceration coefficient, however, did not exhibit the expected impact on the poverty rate difference. According to the model, a one percent increase in the incarceration rate per 100,000 people is expected to decrease the Black-White poverty rate differential by approximately 6.35 points. The coefficient on the cost of living index variable also results in an unexpected sign. According to the model, a 1 point increase in the cost of living index would be expected to yield approximately a .234 point decrease in the poverty rate differential. Additionally, the author finds that the coefficient on the GINI index variable also exhibits the opposite of the hypothesized sign. The model estimates that a one percentage point increase in the GINI coefficient would be expected to yield approximately a .801 point decrease in the poverty rate differential. An F-Test for joint significance finds that the vector of indicator controls for region are jointly significant at the 10% level.

Possible Explanation of the Incarceration Rate Relationship

As previously stated, an increase in incarceration rates actually caused a decrease in the difference between Black and White poverty rates. This could possibly be explained by the correlation between incarceration and poverty, and the disproportionate incarceration of Black Americans. Intuitively, it makes sense that people living in poverty would be more likely to be incarcerated, since their socioeconomic status may make them more likely to resort to crime. Additionally, once a person becomes incarcerated, they are no longer counted into the poverty rate. Therefore, it is not unreasonable to assume that higher incarceration rates may be associated with lower poverty rates, since incarcerated individuals that were previously counted into the poverty rate are no longer factored in. Also, it is relatively well-documented and well-known that Black individuals are incarcerated more frequently than White individuals. Therefore, this combined with the knowledge that incarceration rates may in fact decrease poverty rates, we can assume that higher incarceration rates would decrease Black...
poverty rates more than White poverty rates, thus decreasing the difference between the two.

**Possible Explanation of the Cost of Living Index Relationship**

A negative relationship between the cost of living index and the difference in Black and White poverty rates seems slightly counterintuitive, and is more difficult to explain. This relationship implies that, the more expensive a state is, the smaller the gap between Black and White poverty rates. Since the cost of living index does not actually have a direct relationship with poverty rates (a classification of poverty is determined by income within a given year relative to number of members within a household), this relationship is most likely due to the fact that poverty rates are simply higher amongst White households in states with higher costs of living relative to Black households. Additionally, the author finds that there tends to be a higher population of White individuals in states with a higher cost of living index than Black households, which also may contribute to the nature of this relationship. The slightly complex interpretation of this variable may mean that its actual anecdotal significance may not be extremely relevant.

**Possible Explanation of the GINI Coefficient Relationship**

Model 1 suggests that there is in fact a negative relationship between the difference in poverty rates amongst Black and White households and the value of the GINI coefficient. In essence, this means that the magnitude of the effect of the GINI coefficient on poverty rates is higher amongst White households than amongst Black households. This could possibly be explained by the nature of what an increase in income inequality generally means an increase in the number of wealthy members of the population. Of these increased number of wealthy households, income demographics data suggest that the majority of them will be predominantly White. Therefore, an increase in income inequality is likely a “redistribution” of wealth skewed towards wealthy white households. Since increased income inequality generally increases the poverty rate, and increased income inequality is generally a reallocation of wealth towards high-income White households, it may be reasonable to assume that an increase in the GINI coefficient would have a larger impact on White households than Black households, and thus have a higher impact on White poverty rates. In summary, there is some evidence that a higher level of income inequality would actually be expected to reduce the magnitude of the difference between Black and White poverty rates by state, in 2010. Again, this result is subject to the limitations of the model, described in the previous section.

**Results for Model 2**

A regression of the pre-described format of model 2 results in a statistical significance at the 1% level for the Incarceration and cost of living index coefficients, significance at the 5% percent level for the educational differential coefficient, and significance at the 10% level for the coefficients corresponding to the unemployment rate differential and the distribution variance variables. The independent variables present in model 2 that were also present in model 1 exhibit the same signs of relatively similar magnitude. The primary difference between model 1 and 2 is that the coefficient on the distribution variance variable yields an opposite impact on poverty rate differentials than the GINI coefficient had in model 1. According to model 2, a one
percent increase in a state’s population’s variance from a perfectly equitable distribution would be expected to yield approximately a 5.87 point increase in the difference between Black and White poverty rates. Although this was the expected sign, the contrary result to that of the GINI coefficient impact is notable. As with model 1, the vector of regional controls is jointly significant at the 10% level.

**Interpretation of the Distribution Variance Relationship**

The results from model 2 suggest that there is some evidence that a more varied allocation of a population into each income bracket may increase the difference between Black and White poverty rates. As briefly described previously, this may be due to a larger cluster of the Black population into lower income brackets. An increased distribution variance implies clusters within particular income groups, and an increased severity of these clusters is probably skewed towards the lower income brackets, of which they are expected to be predominately black. Therefore, a higher distribution variance may mean a higher cluster of the Black population within lower income groups, which would be expected to increase poverty rates, thus increasing the Black-White poverty rate differential.

**Conclusions**

Using the information provided from the estimation of the two models, the author determines that there is some evidence that, in 2010, a higher GINI coefficient for a particular state corresponded with a decrease in the difference between Black and White poverty rates, possibly due to the disparity of Black high income earners to White high income earners. The author also concludes that there is some evidence that increased incarceration rates by state, in 2010, actually corresponded with a smaller magnitude in the difference between Black and White Poverty rates, since increasing incarceration rates actually corresponds with a decrease in the Black poverty rate, because impoverished individuals that become incarcerated are no longer counted in the poverty rate. Additionally, the author finds some evidence that there is a positive relationship between the proposed “distribution variance” and the Black-White poverty rate differential, likely due to the larger and more severe clusters of the black population amongst lower income brackets. It should be noted that, in order to obtain a more accurate and conclusive determination of the hypothesized conclusions, one would most likely need to collect panel data over the course of several years, since a one year sample likely results in a sample size that is too small to make any type of sweeping conclusions about the overall population.
### Tables, Figures and Explanations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>GINI Coefficient</td>
<td>.419</td>
<td>.532</td>
<td>.454</td>
<td>.002</td>
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<tr>
<td>Black UE Rate</td>
<td>5.4</td>
<td>23.9</td>
<td>14.53</td>
<td>4.257</td>
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<td>White UE Rate</td>
<td>3.1</td>
<td>13.9</td>
<td>7.87</td>
<td>2.019</td>
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<td>Black EDUC Rate</td>
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<td>12.02</td>
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<td>White EDUC Rate</td>
<td>11.64</td>
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<td>3.75</td>
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<td>White Poverty</td>
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<td>16.75</td>
<td>10.80</td>
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<td>Black Poverty</td>
<td>9.68</td>
<td>42.64</td>
<td>26.21</td>
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<td>Incarceration Rate</td>
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<td>1082</td>
<td>605.61</td>
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<td>GDP per Capita</td>
<td>32177.43</td>
<td>171305.30</td>
<td>48398.89</td>
<td>19603.83</td>
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<td>Cost of Living</td>
<td>89.21</td>
<td>165.56</td>
<td>104.65</td>
<td>16.275</td>
</tr>
</tbody>
</table>

(Table 1)

**Proposed Supplementary Model:**

\[ \ln(\text{GDPC}) = \beta_0 + \beta_1 \ln(\text{DistVar}) + \beta_2 \ln(\text{population}) + \beta_3 (\text{Unemployment Rate}) + \beta_4 (\text{Poverty Rate}) + \beta_{VR}(X_R) \]

Model is limited and most likely not an accurate measurement of the true variability in the GDP per capita of each state, however the author finds that a one percent increase in the distribution variance corresponds with a .835% decrease in GDP per capita, statistically significant at the one percent level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UEDiff</td>
<td>.485** (.241)</td>
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<tr>
<td>ln(GDPC)</td>
<td>-1.717 (3.363)</td>
</tr>
<tr>
<td>EDUCDiff</td>
<td>.578** (.235)</td>
</tr>
<tr>
<td>ln(Incarerate)</td>
<td>-6.351** (2.324)</td>
</tr>
<tr>
<td>COL</td>
<td>-.239*** (.069)</td>
</tr>
<tr>
<td>GINI</td>
<td>-.801* (.410)</td>
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</tbody>
</table>

(Table 2)

*Indicates significant at 10%
**Indicates significant at 5%
***Indicates significant at 1%

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UEDiff</td>
<td>.398* (.240)</td>
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<tr>
<td>ln(GDPC)</td>
<td>-2.183 (3.196)</td>
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<tr>
<td>EDUCDiff</td>
<td>.522** (2.253)</td>
</tr>
<tr>
<td>ln(Incarerate)</td>
<td>-7.331*** (2.452)</td>
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<td>COL</td>
<td>-.239*** (.068)</td>
</tr>
<tr>
<td>ln(DistVar)</td>
<td>5.871* (3.447)</td>
</tr>
</tbody>
</table>

(Table 3)

*Indicates significant at 10%
**Indicates significant at 5%
***Indicates significant at 1%
References


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