Income Inequality Metrics and Economic Well-Being in U.S. Metropolitan Statistical Areas

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Abstract

The purpose of this paper is to examine how the choice of a particular method for measuring income inequality affects the level of income inequality observed in Metropolitan Statistical Areas (MSAs) and the relationship between income inequality and measures of economic well-being. Data from the U.S. Census Bureau's 2014 American Community Survey is used to calculate nine after-tax household income inequality metrics for MSAs. The income variable is adjusted by the size and composition of the household and by MSA cost of living.

There are three types of income inequality metrics used in this paper. Summary measures are the first type: the Gini Index, the Theil Index, and the Mean Logarithmic Deviation of Income. These are single values meant to represent the variability in the income distribution. Distribution-wide income ratios are the second type: the 80:20 ratio, the Palma ratio, and the 90:10 ratio. These measures focus on comparing the top of the income distribution with the bottom of the income distribution, while losing information on the middle of the distribution. Income ratios that cover different parts of the income distribution are the third type: the 99:90 ratio, the 90:50 ratio, and the 50:10 ratio. These metrics allow us to find out where inequality in the income distribution is taking place.

Two main research questions are addressed in this paper. First, how does the use of different inequality metrics affect the interpretation of income inequality among MSAs? While research has been done on this question, little has been done at the MSA level. Second, how does the use of different metrics affect our understanding of economic well-being? Little research has been done on the effect of the choice of an inequality metric on the relationships between income inequality and economic well-being.

Introduction

Income inequality as a concept is straightforward. Are there a lot of haves and have-nots or do most people have close to the same amount of money? However, the measurement of income inequality is not so straightforward. There are a number of different income inequality metrics available and the choice of a particular metric alters the conclusions about the level of income inequality and the relationship between income inequality and economic well-being. Furthermore, each metric has some qualities which make it better at measuring certain aspects of income inequality and worse at measuring other aspects.

The Census Bureau publishes a number of income inequality estimates in the annual report on Income and Poverty in the United States. The Gini Index, the Theil Index, the mean logarithmic deviation of income (MLD), the Atkinson Index, income at selected percentiles, selected income ratios, mean household income of quintiles, and shares of household income of quintiles are all included (DeNavas-Walt 2015). The estimates in this paper differ from these published estimates due to differences in how income is defined. Most Census estimates use before-tax household income, which is not adjusted for cost of living differences or for the size and composition of the household, while the income concept in this paper is after-tax household income adjusted for both cost of living and household size and composition.

This is not the first paper to suggest that additional measures of income inequality may be useful. Analysis of income inequality has been done at the state level using different income inequality metrics. One paper addressed how the Gini Index, Theil Index, MLD, and Atkinson Index compare to one another (Hisnanick 2005) and another paper (Braun 1988) has looked at how the Gini Index, Theil Index, Atkinson, Nelson Index, and coefficient of variation are correlated with state-level characteristics.

Previous authors have also found that the use of different inequality metrics can lead to different conclusions. Krozer (2015) found that the true nature of income inequality is obscured when the Gini Index is used due to its insensitivity to the extremes of the income distribution. Similarly, Gastwirth (2014) found that the Gini Index underestimates income inequality in both the U.S. and Sweden.

However, there is disagreement over how much inequality metrics actually matter. A prime example is in the health literature. Kawachi and Kennedy (1997) examined how six different measures of income inequality were correlated with mortality indicators. They found that the six measures were highly correlated with each other and with mortality. Their conclusion was that the choice of income inequality metric does not matter when looking at the health effects of income inequality.

In the economics literature, Abdullah, Doucouliagos, and Manning (2015) performed a meta-analysis of the effect of education on income inequality based on over sixty studies. They found significant variation in use of income inequality metrics: 48 percent of studies used the Gini Index, 15 percent used Theil, 30 percent used income shares of a particular quintile, 6 percent used the 80:20 ratio, and 2 percent used other measures. However, the end result was a negative effect of educational attainment on income inequality regardless of metric chosen.

There have also been a number of studies lining up on the other side. In the health literature, Weich et al. (2002) found that the Gini index was correlated with poor health among people from low-income groups, but there was no significant relationship when the Theil Index or the MLD was used as the measure of income inequality. The same relationship pattern was observed in De Maio (2005), which looked at the relationship between life expectancy and income inequality.

In the economics literature, there is tremendous disagreement over the effect of income inequality on economic growth. Studies have found the effect to be negative (Sukiassyan (2007), Tachibanaki (2005), Helpman (2004), Acemoglu (1997), Perotti (1996), Persson and Tabellini (1994)), positive (Forbes (2000), Aghion and Howitt (1998), Li and Zhou (1998), Benabou (1996)), inconclusive (Shin et al. (2009), Weil (2005), Banerjee and Duflo (2003), Barro (2000), Amos (1998)), or nonexistent (Deininger and Squire (1996) and Binatli (2012)). The differences in conclusions in these studies are based on design: different countries, different years, and most important for this paper, different income inequality metrics.

To summarize, the effects of income inequality metrics on conclusions about income inequality and economic well-being are not well settled in the literature. To address these discrepancies, the focus in this paper is exclusively on these unsettled areas rather than treating the use of a different metric as a side issue or a robustness check.

Data from the U.S. Census Bureau's 2014 American Community Survey is used to calculate nine after-tax household income inequality metrics for metropolitan statistical areas (MSAs). Household after-tax income includes wages and salary income, self-employment income, retirement income, interest and dividends, as well as transfer payments (Supplemental Security Income, Social Security and public assistance) and subtracts federal and state taxes using the National Bureau of Economic Research's TAXSIM Program[1].

[1] Feenberg, Daniel Richard, and Elizabeth Coutts. 1993. "An Introduction to the TAXSIM Model". *Journal of Policy Analysis and Management* 12(1): 189-194. http://www.nber.org/taxsim/.

The income variable is adjusted by the size of the household using a three-parameter equivalence scale[2] and then adjusted by MSA cost of living using factors developed by the Bureau of Economic Analysis (BEA)[3]. The nine inequality metrics used in this paper are:

- Gini Index — A statistical measure of income inequality ranging from zero, perfect equality, to one, perfect inequality.
- Theil Index – A measure of distance that the population is away from perfect equality. The measure starts at zero, perfect equality, and is unbounded from above.
- Mean Logarithmic Deviation of income (MLD)– A measure of how much each household's income differs from mean income. The measure starts at zero, perfect equality, and is unbounded from above.
- Palma Ratio — Ratio of top 10 percent share to lowest 40 percent share of total income.
- Household income ratios of selected percentiles:
    - 80:20 ratio — 80th percentile income limit divided by 20th percentile income limit.
    - 90:10 ratio — 90th percentile income limit divided by 10th percentile income limit.
    - 90:50 ratio — 90th percentile income limit divided by 50th percentile income limit.
    - 50:10 ratio — 50th percentile income limit divided by 10th percentile income limit.
    - 99:90 ratio — 99th percentile income limit divided by 90th percentile income limit.

Research Questions

Two main research questions are addressed in this paper. First, how does the use of different inequality metrics affect the interpretation of income inequality among MSAs? To answer this question, I calculate nine income inequality metrics by MSA, compare them to each other, and examine how the use of different metrics leads to different conclusions about the nature of income inequality. Second, how does the use of different metrics affect our understanding of economic well-being? To answer this question, I look at the relationships between a number of measures of economic well-being and the nine income inequality metrics.

[2] Short, Kathleen. 2014. "The Supplemental Poverty Measure: 2013". *Current Population Reports*. U.S. Census Bureau.
[3] http://www.bea.gov/newsreleases/regional/rpp/rpp_newsrelease.htm.

Data

The household data used in the paper comes from the 2014 American Community Survey (ACS) one-year estimates.[4] This research is restricted to heads of households who live in an identifiable metropolitan statistical area (MSA). The dataset consists of 1.65 million households who live in 381 MSAs. All coefficients are calculated using household weights and standard errors are calculated using replicate weights. This dataset is augmented with MSA characteristics from Sperling's Best Places[5], BEA regional price parities[6], BEA Regional Economic Accounts[7], the U.S. Census Bureau's Annual Estimates of the Resident Population[8], and data from the Equality of Opportunity project[9].

The main variable of interest throughout the paper is household after-tax income. Household after-tax income includes wage and salary income, self-employment income, retirement income, interests and dividends, and transfer payments (Supplemental security income, social security, and cash public assistance) and subtracts federal and state taxes using the National Bureau of Economic Research's TAXSIM program.[10] Due to tax credits, it is possible for taxes to be negative, which means that income will increase for these people after taxes are taken into account.

The difference in household size is adjusted for by using the following three-parameter equivalence scale, which is the same equivalence scale used in the supplemental poverty measure[11]:

One and two adults: $scale = adults\text{^}0.5$

Single parents: $scale = (adults + 0.8 \times first\ child + 0.5 \times other\ children)\text{^}0.7$

All other families: $scale = (adults + 0.5 \times children)\text{^}0.7$

where adults is the number of adults in the household, first child is equal to one if the household has at least one child, other children is equal to the number of children in the household minus one, and children is the number of children in the household.

Income is divided by this scale variable to get a measure of equivalence adjusted household income. Finally, income is adjusted by MSA cost of living (COL) using regional price parities (RPPs) developed by the Bureau of Economic Analysis (BEA). RPPs are based on prices of a variety of items

[4] For more information on the ACS, see census.gov/acs.
[5] www.bestplaces.net.
[6] http://www.bea.gov/newsreleases/regional/rpp/rpp_newsrelease.htm.
[7] http://bea.gov/regional/index.htm.
[8] http://www.census.gov/popest/.
[9] http://www.equality-of-opportunity.org/.
[10] Feenberg, Daniel Richard, and Elizabeth Coutts. 1993. "An Introduction to the TAXSIM Model". *Journal of Policy Analysis and Management* 12(1): 189-194. http://www.nber.org/taxsim/.
[11] Short, Kathleen. 2014. "The Supplemental Poverty Measure: 2013". *Current Population Reports*. U.S. Census Bureau.

from the Consumer Price Index, such as food, transportation, and education, as well as rents obtained from the American Community Survey. These prices and rents are used to create an index which compares each MSA price level to the national price level. Descriptive statistics are listed in Table 1.

Table 1: Equivalence and COL Adjusted Household Income				
	Mean	Std. Err.	Median	Std. Err.
Pre-tax, pre-transfer income	$41,287.52	$45.95	$30,027.91	$33.99
Pre-tax, after-transfer income	$45,239.48	$45.42	$33,739.42	$37.08
After-tax, after-transfer income	$42,943.83	$37.79	$33,701.00	$33.94

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

Descriptive statistics for economic and demographic characteristics are presented in Table 2.

- The tax rates are combined state and local total tax rates.
- The total crime variable, which is an index from zero to two hundred, is created by adding together violent crime, an index from zero to one hundred, and property crime, an index from zero to one hundred.
- Economic growth is the percentage change in real GDP from 2013 to 2014 in each MSA.
- Population growth is the change in MSA population from 2013 to 2014.
- Skills mix is a ratio of the percentage of people in an MSA with a college degree to the percentage of people in an MSA without a high school degree.
- Generational mobility is a measure of how much a child's economic standing is explained by his or her parent's economic standing. In statistical terms, it is the coefficient from an OLS regression of child rank on parent's rank in terms of where each falls in an income distribution. A lower value of mobility means that less of a child's outcome is explained by a parent's outcome. Therefore, more potential for economic mobility exists.

Table 2: Economic and Demographic Characteristics of MSAs: 2014				
	Mean	**Std. Err**	**Minimum**	**Maximum**
Income Tax Rate[B]	4.38	0.13	0.00	9.58
Sales Tax Rate[B]	6.93	0.09	0.00	10.00
Cost of Living[D]	94.45	0.38	78.00	122.50
Economic Growth[C]	1.46	0.12	-6.34	20.26
Poverty[A]	15.32	0.20	7.58	32.13
Unemployment[A]	6.80	0.13	1.96	31.56
Total Crime[B]	91.05	1.29	29.30	164.70
Population[E]	715,619	83,767	54,522	20,092,883
Population growth[E]	0.70	0.05	-2.15	6.81
Generational Mobility[F]	0.33	0.003	0.17	0.43
Skills mix[A]	3.64	0.14	0.43	22.62

Source: A - 2014 American Community Survey. For more information on the ACS, see census.gov/acs. B - Sperling's Best Places. C - BEA Regional Economic Accounts. D - BEA Regional Price Parities. E – U.S. Census Bureau's Annual Estimates of the Resident Population. F – Equality of Opportunity project.

Definitions and Methodology

The income inequality metrics used in the analysis in this paper are broken up into three general categories. The first category are summary measures. These include the Gini Index and the generalized entropy measures.

The Gini Index is the most well known and often used measure of income inequality. The Gini sums up the absolute differences between each pair-wise comparison of household income. This gives a statistical measure of income inequality ranging from zero, perfect equality, to one, perfect inequality.

While the Gini offers ease of interpretation and the ability to easily compare among different geographical areas, it does have some limitations. First, while the Gini index can show that income inequality exists, it does not give any information about where in the income distribution the inequality exists. For example, it is possible for two MSAs to have Gini indexes that are not statistically different, but for one MSA to have more inequality in the top half of the income distribution while the other MSA has more inequality in the bottom half of the income distribution. These are important distinctions, which the Gini index fails to capture.

Second, the Gini index is over-sensitive to changes in household income towards the middle of the distribution and not sensitive enough to changes in household income at the lower and upper portions of the income distribution (Krozer (2015), Hasenheit (2014)). This means that the Gini Index could be unchanged or even show less inequality while societal income is becoming more polarized.

The generalized entropy measures are the Theil Index and the Mean Logarithmic Deviation of Income (MLD). Both of these measures, like the Gini index, are summary measures of income dispersion. However, the Theil Index is more sensitive to changes that affect the upper part of the income distribution, while the MLD is more sensitive to changes that affect the lower part of the income distribution (World Bank Institute 2005). Furthermore, unlike the Gini Index, neither of these measures is bounded from above. The main limitation for these measures is that they are both calculated using the natural log which means they are undefined for income less than or equal to zero.

The second category of income inequality metrics are income ratios. Income ratios attempt to get a picture of different parts of the income distribution. The first of these metrics is the Palma Ratio. This measure is calculated by dividing the total income earned by households in the top 10 percent of the income distribution by the total income earned by households in the bottom 40 percent of the income distribution. This ratio is used for two reasons. First, the 50 percent of income earners between the fifth decile and ninth deciles have been found to have a relatively stable share of income both across countries and time (Palma 2005). Therefore, inequality can be summarized with this ratio without losing much information. Second, the Palma ratio is only sensitive to changes at the top and bottom of the distribution. In that way, it provides a useful counter to the Gini Index.

The next metric is called the 80:20 ratio. This ratio compares how much richer the top 20 percent of households are compared to the bottom 20 percent of households. This metric is calculated by dividing the income at the top quintile cutoff point by the income at the bottom quintile cutoff point. This ratio ignores the effect of the middle 60 percent, which tends to be stable and less interesting economically.

The third category of metrics look at non-overlapping parts of the income distribution and are calculated using the same methods as the 80:20 ratio. These metrics are the 90:10 ratio and the 99:90 ratio. The 90:10 ratio is then further broken down into the 90:50 ratio and the 50:10 ratio. Each of these ratios show what is happening at different parts of the income distribution and thus provide a richer view of income inequality then a simple summary measure. This is not to say that the income ratios are perfect either. For example, there could be all kinds of changes taking place between the 51st and 89th percentiles, but these changes are not reflected in the 90:50 ratio.

Discussion and Results

The main idea addressed in this paper is how the use of different income inequality metrics affects our understanding of income inequality. To break this idea into more manageable pieces, two questions are explored. First, how do different income inequality metrics compare to one another? Second, how does the relationship between economic well-being and income inequality change with the use of these different income inequality metrics?

Question 1: How do the different metrics compare to one another?

In order to make the answer to this first question more manageable, it is further divided into three areas. First, how do the adjustments made to household income affect the income inequality metrics? Second, how is income inequality in individual MSAs affected by the use of different inequality metrics? Third, how do the income inequality metrics compare and contrast with one another overall?

1.A: Effects of adjustments to Household Income

As mentioned in the data section, the main variable of interest throughout the paper is after-tax household income, which includes government cash transfers, is adjusted for cost of living, and is adjusted by the size of the household. However, these adjustments are important choices, which have a real effect on the level of income inequality that is observed. Furthermore, each of these adjustments may have a disparate impact depending on the inequality metric used.

To address these issues, the effect of government policies is examined in Table 3 and the effect of data user adjustments is examined in Table 5. In Table 3, three sets of coefficients are presented. The first set is before-tax household income net of any social security, public assistance, and supplemental security income that the household received. The second set adds the government transfers back into household income, but leaves taxes out. The third set subtracts federal taxes and state taxes (and adds tax credits) from after-transfer household income. This enables us to look at three effects: just transfer payments, just taxes, and taxes and transfer payments together.

Table 3: Effect of Taxes and Transfers

	Pre-tax, pre-transfer (1)		Pre-tax, after-transfer (2)		After-tax, after-transfer (3)	
Metric	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**
Gini	0.4705	0.00044	0.4466	0.00041	0.4173	0.00035
Theil	0.4321	0.00124	0.3905	0.00113	0.3310	0.00085
MLD	0.6174	0.00157	0.5238	0.00138	0.4565	0.00124
80:20	4.9636	0.00021	4.2392	0.00013	3.7632	0.00009
Palma	2.9921	0.00393	2.5487	0.00372	1.8835	0.00350
90:10	13.6935	0.00094	9.5483	0.00050	8.8014	0.00036
50:10	5.1115	0.00016	3.6930	0.00008	3.3496	0.00007
90:50	2.6790	0.00005	2.5855	0.00005	2.4127	0.00004
99:90	2.6891	0.00011	2.6419	0.00011	2.4337	0.00008
Adjustments:						
Taxes	No		No		Yes	
Transfers	No		Yes		Yes	
Equivalence	Yes		Yes		Yes	
Cost of living	Yes		Yes		Yes	

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

Since each metric is measured on a different scale, Table 4 lists the percentage change in each metric due to transfers, taxes, and taxes and transfers together in order to make comparisons. The government programs in Table 4 are designed to redistribute income from those in the upper end of the income distribution (taxes) to those in the lower end of the income distribution (tax credits and transfers).

It should come as no surprise that each percentage change in Table 4 is negative and statistically significant. Transfers increase incomes for those at the lower end of the income distribution in column 1, taxes progressively reduce income for many people and tax credits increase income for some people in column 2, and the full effect of redistribution is shown in column 3. Each of these effects will necessarily lead to decreased income inequality. However, the magnitude of each metric's response to these income adjustments varies considerably.

Table 4: Percentage Change in Inequality Metrics						
	Effect of transfers		Effect of taxes		Overall effect	
Metric	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**
Gini	-5.080	0.055	-6.561	0.055	-11.307	0.054
Theil	-9.627	0.155	-15.237	0.123	-23.397	0.122
MLD	-15.160	0.195	-12.848	0.171	-26.061	0.169
80:20	-14.594	0.020	-11.229	0.013	-24.184	0.018
Palma	-14.820	0.484	-26.098	0.435	-37.051	0.428
90:10	-30.271	0.074	-7.8223	0.054	-35.726	0.070
50:10	-27.751	0.018	-9.299	0.014	-34.469	0.017
90:50	-3.490	0.011	-6.683	0.006	-9.940	0.010
99:90	-1.755	0.014	-7.881	0.014	-9.498	0.014

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

The responses of the three summary measures are as expected given their definitions. The Gini index is sensitive to changes in the middle of the distribution and not very sensitive to changes at the tails. Compared to the other two summary measures, the Gini index decreases less in response to taxes and transfers. The Theil index, which is more sensitive to changes at the top of the income distribution, shows a smaller effect of transfers than the MLD, which is more sensitive to changes at the bottom of the income distribution, and a larger effect of taxes than the MLD.

The responses of the income ratios to these adjustments are significantly varied as well. The most interesting results are the three non-overlapping parts of the distribution: the 50:10, the 90:50, and the 99:90. Transfer benefits largely accrue to the bottom of the income distribution, which is why we see a large effect of transfers on the 50:10 ratio and small effects on the other two ratios. The tax system is progressive in nature. We see a larger effect on income inequality in the bottom half of the income distribution than in the top half of the income distribution. When looking overall, the effect of government programs is a large decrease in inequality at the bottom of the income distribution (50:10 ratio) and a modest decrease in inequality in the upper half of the income distribution (99:90 and 90:50 ratios).

As mentioned in the Data section, the household income variable is adjusted for differences in cost of living among MSAs and differences in the size of households. Table 5 displays three different models, which can be compared to each other and to the after-tax, after-transfer coefficients in Table 3.

Table 5: Effect of Equivalence and Cost of Living Adjustments						
	Model 1 – No equivalence adjustment		Model 2 – No cost of living adjustment		Model 3 – No equivalence or cost of living adjustment	
Metric	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**
Gini	0.4422	0.00033	0.4235	0.00036	0.4488	0.00034
Theil	0.3628	0.00080	0.3415	0.00088	0.3748	0.00084
MLD	0.5101	0.00127	0.4646	0.00125	0.5201	0.00128
80:20	4.3930	0.00012	3.8098	0.00009	4.4582	0.00012
Palma	2.1653	0.00323	1.9499	0.00346	2.2517	0.00316
90:10	10.4206	0.00045	8.2267	0.00039	10.7074	0.00048
50:10	3.9131	0.00008	3.3353	0.00008	3.9304	0.00008
90:50	2.6630	0.00004	2.4665	0.00004	2.7243	0.00004
99:90	2.3712	0.00007	2.4758	0.00008	2.4172	0.00007
Adjustments:						
Taxes	Yes		Yes		Yes	
Transfers	Yes		Yes		Yes	
Equivalence	No		Yes		No	
Cost of living	Yes		No		No	

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

In Table 6, the percentage change in each metric is presented for the effect of adjusting for MSA cost of living (Model 3 vs. Model 1), the effect of adjusting for the size of the household (Model 3 vs. Model 2), and the effect of both adjustments together (Model 3 vs. after-tax, after-transfer coefficients in Table 1).

Table 6: Percentage Change in Inequality Metrics						
	Effect of COL		Effect of Equivalence		Overall effect	
Metric	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**
Gini	-1.471	0.042	-5.637	0.049	-7.019	0.049
Theil	-3.202	0.111	-8.885	0.116	-11.686	0.107
MLD	-1.923	0.182	-10.671	0.167	-12.228	0.166
80:20	-1.463	0.014	-14.544	0.013	-15.589	0.013
Palma	-3.838	0.443	-13.403	0.441	-16.353	0.438
90:10	-2.679	0.070	-23.168	0.056	-17.801	0.057
50:10	-0.440	0.014	-15.141	0.013	-14.777	0.013
90:50	-2.250	0.060	-9.463	0.005	-11.438	0.005
99:90	-1.903	0.014	2.424	0.091	0.683	0.014

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

There is a statistically significant negative effect on each metric when adjusting for cost of living. There is a smaller effect of geographic adjustments on inequality at the bottom of the income distribution (50:10) then on inequality at the top of the distribution (90:50). Compared to the cost of living adjustment, there is a significantly larger effect, in absolute value, on each metric of using the equivalence scale to adjust for the size and composition of the household. Equivalence adjustment has a much larger effect on inequality at the bottom (50:10) as compared to the top of the income distribution (90:50), while cost of living has a larger effect on inequality in the top of (90:50) as compared to the bottom (50:10) of the income distribution. However, equivalence adjustment actually increases inequality among the top 10 percent of the income distribution (99:90).

1.B: Comparison of inequality metrics for select MSAs

In this section, a selection of MSAs are examined in order to see how the use of different income inequality metrics can affect our perceptions of the level of income inequality at the MSA level. Each income inequality metric is based on after-tax, after-transfer household income adjusted for cost of living and for size of household. The nine income inequality metrics are calculated for each individual MSA.

In Table 7, four MSAs are chosen in order to provide a snapshot of the 381 MSAs in this study. Washington, DC and Cincinnati, OH are picked because the difference in their Gini Indexes is not statistically significant. This allows us to look at differences and similarities between the other metrics, given that the differences in the Gini's are not statistically significant. For the same reasons, Cincinnati, OH and Denver, CO are chosen for the Palma ratio and Denver, CO and Dothan, AL are chosen for the 90:10 ratio.

Table 7: Selection of City Comparisons

	Washington, DC		Cincinnati, OH		Denver, CO		Dothan, AL	
Metric	**Estimate**	**Std. Err.**	**Estimate**	**Std. Err.**	**Estimate**	**Std. Err.**	**Estimate**	**Std. Err.**
Gini	0.3767	0.0020	0.3766	0.0037	0.3786	0.0350	0.3884	0.0087
Theil	0.2601	0.0036	0.2690	0.0078	0.2750	0.0080	0.2951	0.0214
MLD	0.3607	0.0072	0.4214	0.0133	0.3851	0.0112	0.4465	0.0340
80:20	3.4119	0.0005	3.3206	0.0014	3.2091	0.0010	3.4563	0.0076
Palma	1.6658	0.0219	1.7113	0.0391	1.7202	0.0325	1.8367	0.0961
90:10	6.7970	0.0016	7.0032	0.0052	6.2616	0.0034	6.2897	0.0324
50:10	3.1530	0.0004	3.2160	0.0012	2.8928	0.0008	2.7790	0.0079
90:50	2.1557	0.0001	2.1776	0.0005	2.1645	0.0004	2.2633	0.0028
99:90	2.0614	0.0004	2.1407	0.0012	2.2647	0.0011	2.4215	0.0072

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

In Table 8, the difference in the coefficients for the MSA pairs are listed. If there is a "-" sign in the column, then there is no significant difference at the 10 percent level between the coefficients. If A > B is listed in the column, then MSA A has higher income inequality than MSA B according to the metric.

If A < B is listed in the column, then MSA A has lower income inequality than MSA B according to the metric.

Table 8: Difference in Coefficients for MSA pairs				
	1	**2**	**3**	**4**
	DC – CINC	**DC – Denver**	**CINC – Denver**	**Denver - Dothan**
Gini	-	-	-	-
Theil	-	DC < Denver	-	-
MLD	CINC > DC	DC < Denver	CINC > Denver	Denver < Dothan
80:20	CINC < DC	DC > Denver	CINC > Denver	Denver < Dothan
Palma	-	-	-	-
90:10	CINC > DC	DC > Denver	CINC > Denver	-
50:10	CINC > DC	DC > Denver	CINC > Denver	Denver > Dothan
90:50	CINC > DC	DC < Denver	CINC > Denver	Denver < Dothan
99:90	CINC > DC	DC < Denver	CINC < Denver	Denver < Dothan

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

As shown in Table 8, some metrics show no significant difference in inequality in two MSAs, some show greater inequality in one MSA, and some show greater inequality in the other MSA. This seriously complicates matters when trying to either rank MSAs based on levels of income inequality or select a single income inequality metric for analysis.

To delve deeper, there are interesting differences in the summary measures and in the income ratios looking at different parts of the income distribution. Column one and column three of Table 8 show similar patterns for the summary measures. The Gini indexes and Theil Indexes are not statistically different in both columns, while the MLD are statistically different. If one used the MLD for analysis, one would conclude that Cincinnati, OH has higher income inequality than Washington, DC and Denver, CO. However, if one were to use the Gini or the Theil, one would conclude that there is no statistically significant difference in income inequality between the three MSAs.

Another interesting result shows up in columns two and four of Table 8. In both of these columns, the 90:50 ratio and the 50:10 ratio have different signs. For example, if one used the 90:10 ratio for analysis, one would conclude that Washington, DC has more income inequality than Denver, CO. However, that conclusion only holds for the bottom half of the income distribution (90:50).

Similarly, in column four one would conclude that Denver, CO and Dothan, AL do not have significant differences in income inequality if the 90:10 ratio is used. However, Dothan, AL has higher income inequality in the top of the income distribution (90:50 ratio and 99:90 ratio), while Denver, CO has higher income inequality in the bottom of the income distribution (50:10 ratio).

Related to the analysis in Tables 7 and 8, it is often useful to be able to rank MSAs in terms of levels of income inequality. Due to either small differences in inequality metrics or large standard errors, a complete MSA ranking for each metric is not possible. However, a ranking is possible for large MSAs. Large MSAs consist of the 53 MSAs with populations greater than one million people in 2014. In Table 9, the ten largest MSAs are listed by size of population. Under each income inequality column, the rank order from 1 to 53 is listed, with 1 corresponding to highest income inequality and 53 corresponding to lowest income inequality. The Gini index, Theil index, Palma Ratio and MLD are not shown because the coefficients are not statistically different enough to create ranks.

Table 9: Inequality Ranks among Large MSAs

Ten largest MSAs	80:20	90:10	90:50	50:10	99:90
New York, NY	1	1	4	1	2
Los Angeles, CA	2	4	2	20	7
Chicago, IL	14	13	16	14	12
Dallas, TX	12	17	9	32	4
Houston, TX	4	7	3	30	10
Philadelphia, PA	15	9	22	4	23
Washington, DC	22	33	38	25	51
Miami, FL	6	3	1	19	1
Atlanta, GA	22	21	10	35	27
Boston, MA	10	8	24	3	6

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

Other than New York, there is a significant amount of variation in income inequality ranks depending on the income inequality metric used. For instance, Dallas has fairly steady rankings among the top 20 except for the 50:10 ratio in which it is closer to the middle of the pack. Houston has rankings in the top 10 except for the 50:10 ratio. Los Angeles also has rankings in the top ten except for the 50:10 ratio. Boston has top 10 rankings except for the 90:50 ratio at 20 and the 50:10 ratio at 4 and Miami has top 5 rankings for every metric except for the 50:10.

These individual rankings make clear that the 80:20 ratio and the 90:10 ratio lose information about different parts of the income distribution and become average effects. These distribution-wide income ratios can tell us a lot about the absolute level of income in equality, but they cannot tell us what life is like in these MSAs because they say nothing about where the income inequality is taking place.

1.C: Comparison of inequality metrics for all MSAs

In Table 10, income inequality metrics are calculated for each MSA and then an unweighted correlation between each metric pair is calculated along with a standard error for the correlation in parentheses. All correlations are statistically significant at the 5 percent level.

Table 10: Correlations Among Inequality Metrics

	Gini	80:20 ratio	Palma ratio	90:10 ratio	90:50 ratio	50:10 Ratio	99:90 ratio	Theil	MLD
Gini	1	0.7870 (0.0317)	0.9752 (0.0114)	0.6851 (0.0374)	0.8343 (0.0283)	0.4714 (0.0453)	0.5295 (0.0436)	0.9369 (0.0180)	0.6758 (0.0379)
80:20 ratio		1	0.8031 (0.0306)	0.8676 (0.0255)	0.7240 (0.0326)	0.7273 (0.0353)	0.0785 (0.0512)	0.6479 (0.0391)	0.7620 (0.0333)
Palma ratio			1	0.7399 (0.0346)	0.8204 (0.0294)	0.5377 (0.0433)	0.5329 (0.0435)	0.9552 (0.0152)	0.7774 (0.0323)
90:10 ratio				1	0.6352 (0.0397)	0.9242 (0.0196)	0.0887 (0.0512)	0.5958 (0.0413)	0.7911 (0.0314)
90:50 ratio					1	0.3305 (0.0485)	0.2014 (0.0503)	0.7169 (0.0358)	0.6452 (0.0392)
50:10 ratio						1	0.0123 (0.0514)	0.4070 (0.0469)	0.6841 (0.0375)
99:90 ratio							1	0.6193 (0.0403)	.1908 (.0504)
Theil								1	.7165 (.0358)
MLD									1

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.
Note: Standard errors are in parentheses.

The Gini index is highly correlated with most of the other metrics. The least correlated measures are the 50:10 ratio, the metric focused on the bottom half of the income distribution, and the 99:90 ratio, the metric focused on the very top of the income distribution. Therefore, inequality in the bottom half and at the very top of the income distribution is what researchers may be ignoring when the Gini index is used to represent income inequality. This conforms with the criticism often levied at the Gini that it is sensitive to changes near the middle of the income distribution, but not very sensitive to changes at the top and bottom of the income distribution.

The Theil index, which is sensitive to changes to the top of the income distribution, is more highly correlated with the 99:90 ratio and less highly correlated with the 50:10 ratio than the MLD, which is more sensitive to changes to the bottom of the income distribution. The 90:50 ratio has a low correlation with the 50:10 ratio and with the 99:90 ratio. However, an even lower correlation belongs to the 50:10 ratio and 99:90 ratio.

The point of Table 10 is twofold. First, MSAs may have fairly similar summary measures of income inequality, but income inequality at different parts of the income distribution has a significant amount of variance. Second, even the summary measures and the income ratios covering the majority of the income distribution show significant variation. This has important implications for the use of income inequality metrics in econometric analyses.

Each of the nine inequality metrics is measured in a different way using slightly or even greatly different scales. In Table 11, standardized coefficients of each inequality metric are presented so that they can be compared to each other on the same scale. The metrics are standardized using the following formula:

$$\check{I}_j = \frac{i_j - min(i)}{max(i) - min(i)}$$

where $\check{I}_j$ is the standardized coefficient for MSA j, i_j is the unstandardized coefficient for MSA j, min(i) is the minimum value of i, and max(i) is the maximum value of i. To find the standardized metric, the average of $\check{I}_j$ across MSAs is used. The metrics are on a scale from zero to one with a larger number corresponding to higher income inequality. The metrics are each statistically different from zero and are listed in Table 11.

There are some differences when comparing the metrics to each other. However, the Theil Index and the 50:10 ratio are not statistically different from each other, the 90:50 ratio and the Gini Index are not statistically different from each other, and the Gini Index and the 80:20 ratio are not statistically different from each other. The remaining pair-wise comparisons of metrics show statistically significant differences.

Table 11: Comparison of Average MSA Standardized Metrics

Inequality Metric	Estimate	Std. Err.
99:90	0.1565	0.0040
50:10	0.2204	0.0059
Theil	0.2252	0.0057
Palma	0.2820	0.0077
MLD	0.3024	0.0073
90:10	0.3263	0.0061
90:50	0.3603	0.0087
Gini	0.3703	0.0075
80:20	0.3832	0.0094

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

Although these are standardized metrics with no real interpretation, the estimates can tell us a lot about how we measure inequality. For example, studies that perform analysis and offer conclusions based on the causes and effects of income inequality using the Gini Index would find significantly different results if they used the 80:20 ratio or the Theil index instead. This calls into question any analysis relying on one measure of income inequality because the conclusions may be affected by the choice of an inequality metric. Any study involving income inequality should use multiple metrics in its analysis, at least for robustness checks.

An important next step is to look at how these metrics vary by size of MSA. In Table 12, this is done with three different MSA sizes. There are 53 large MSAs, which consist of MSAs with populations greater than one million people in 2014, 132 medium MSAs, which consist of MSAs with populations between 250,000 and one million people in 2014, and 196 small MSAs, which consist of MSAs with populations less than 250,000 people in 2014.

Rather than calculate overall MSA standardized coefficients like in Table 11, a standardized coefficient is calculated for small MSAs, medium MSAs, and large MSAs. The difference between the large and the medium MSA coefficients and the difference between the medium and the small MSA coefficients are also listed.

Table 12: Standardized Inequality Metrics Across MSAs

Metric	Small	Medium	Large	Large - Medium	Medium - Small	Large - Small
Gini	0.3484^{+}	0.3756^{+}	0.4381^{+}	0.0624^{+}	0.0272*	0.0896^{+}
	(0.0113)	(0.0117)	(0.0143)	(0.0185)	(0.0162)	(0.0182)
Theil	0.2128^{+}	0.2288^{+}	0.2622^{+}	0.0333$^{\alpha}$	0.0160	0.0494^{+}
	(0.0090)	(0.0086)	(0.0100)	(0.0132)	(0.0125)	(0.0135)
MLD	0.2892^{+}	0.3114^{+}	0.3286^{+}	0.0172	0.0223	0.0395$^{\alpha}$
	(0.0111)	(0.0120)	(0.0125)	(0.0174)	(0.0164)	(0.0167)
80:20	0.3633^{+}	0.3865^{+}	0.4482^{+}	0.0616$^{\alpha}$	0.0232	0.0848^{+}
	(0.0142)	(0.0148)	(0.0194)	(0.0244)	(0.0205)	(0.0240)
Palma	0.2626^{+}	0.2870^{+}	0.3415^{+}	0.0545^{+}	0.0244	0.0789^{+}
	(0.0115)	(0.0123)	(0.0156)	(0.0199)	(0.0168)	(0.0194)
90:10	0.3195^{+}	0.3233^{+}	0.3589^{+}	0.0355^{+}	0.0039	0.0394^{+}
	(0.0097)	(0.0090)	(0.0091)	(0.0128)	(0.0132)	(0.0133)
50:10	0.2172^{+}	0.2148^{+}	0.2462^{+}	0.0314^{+}	-0.0023	0.0291$^{\alpha}$
	(0.0101)	(0.0073)	(0.0074)	(0.0104)	(0.0125)	(0.0126)
90:50	0.3397^{+}	0.3723^{+}	0.4062^{+}	0.0339	0.0326*	0.0664^{+}
	(0.0126)	(0.0150)	(0.0177)	(0.0231)	(0.0196)	(0.0217)
99:90	0.1543^{+}	0.1535^{+}	0.1720^{+}	0.0185^{+}	-0.0008	0.0176$^{\alpha}$
	(0.0069)	(0.0052)	(0.0042)	(0.0067)	(0.0087)	(0.0081)

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.

Note: Standard errors are in parentheses. $^{+}$ significance at the 1 percent level; $^{\alpha}$ significance at the 5 percent level; * significance at the 10 percent level

The most important finding in Table 12 is that inequality is higher in larger MSAs according to each metric when comparing large MSAs to small MSAs. This finding also holds for all metrics except for the MLD and the 90:50 ratio when comparing large MSAs to medium MSAs. However, this finding only holds for the Gini Index and the 90:50 ratio when comparing medium MSAs to small MSAs. This is an intuitive result. Bigger MSAs are likely to be more heterogeneous in nature, encompass urban and suburban areas, and put more strain on a city's social services. Each of these factors makes it more likely that bigger MSAs have a greater mix of those at the lower and upper ends of the income distribution. Despite these similarities among metrics, the magnitude of the changes in income inequality among MSA size varies significantly by income inequality metric.

Question 2 – How do the different metrics relate to economic well being?

The second area to explore is how the use of different inequality metrics affects the relationship between income inequality and measures of economic well-being. The answer to this question comes from exploring three tables. The first involves the correlation of MSA characteristics with the three income ratios covering most of the income distribution. This is done to find out the relationships between these factors of economic well-being and income inequality at different parts of the income distribution.

Table 13: Correlations of Income Ratios with Economic Well-Being: 2014

	50:10 Ratio	Std. Err.	90:50 Ratio	Std. Err.	99:90 Ratio	Std. Err.
Economic Growth	-0.0672	0.0513	0.1143$^{\alpha}$	0.0510	0.2584^{+}	0.0496
Population Growth	-0.0014	0.0514	0.2021^{+}	0.0503	0.2018^{+}	0.0503
Income Tax Rate	-0.0245	0.0514	-0.2443^{+}	0.0498	-0.2305^{+}	0.0500
Sales Tax Rate	0.1657^{+}	0.0507	0.2856^{+}	0.0492	0.0983*	0.0511
Cost of Living	0.0655	0.0513	0.1004$^{\alpha}$	0.0511	0.1369^{+}	0.0504
Total Crime	0.1214^{+}	0.0510	0.3341^{+}	0.0484	-0.0174	0.0514
Poverty Rate	0.4732^{+}	0.0453	0.4996^{+}	0.0445	-0.1049$^{\alpha}$	0.0511
Unemployment	0.0843*	0.0512	0.2407^{+}	0.0499	-0.1510^{+}	0.0508
Mean Income	-0.0092	0.0514	-0.0743	0.0512	0.3886^{+}	0.0473
Skills Mix	0.2398^{+}	0.0499	-0.1997^{+}	0.0503	0.0600	0.0513
Generational Mobility	0.1533^{+}	0.0508	-0.0916*	0.0512	-0.0881*	0.0512

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.
Note: $^{+}$ significance at the 1 percent level; $^{\alpha}$ significance at the 5 percent level; * significance at the 10 percent level

Income tax rates are negatively correlated with two of the three metrics, while the relationship between income tax rates and the 50:10 ratio is not statistically significant. Since no causal argument is made, this can have two interpretations. First, MSAs with higher income tax rates have lower income inequality at the top of the income distribution. This may be due to the progressive nature of state and local income tax systems. In addition, areas with high income tax rates may also have more generous transfer payments. Alternatively, MSAs with higher income inequality have lower income tax rates. This may be evidence of wealthy people relocating to areas with favorable income tax systems.

Sales tax rates are positively and significantly correlated with all three metrics. The relationship between sales tax rate and income inequality at the 90th percentile of the income distribution and below (90:50 and 50:10 ratios) is stronger than the relationship between sales tax rate and income inequality at the very top of the income distribution (99:90 ratio). Unlike the income tax rate, the sales tax rate is not progressive. Households at the lower end of the income distribution pay a higher proportion of their income in sales tax than those at the upper end of the income distribution.

Cost of living is positively and significantly correlated with two of the metrics, but there is no significant relationship between sales tax rates and the 50:10 ratio. This means that in more expensive MSAs, income inequality is higher in the top half of the income distribution (90:50 and 99:90 ratios).

Crime is positively correlated with two of the metrics and the relationship between crime and the 99:90 ratio is not statistically significant. Therefore, higher income inequality over the majority of the income distribution is associated with higher crime rates.

As shown in Table 13, poverty and unemployment have the same pattern of relationships with the three income inequality metrics. Both are positively and significantly correlated with income inequality at the top half (90:50 ratio) and the bottom half (50:10 ratio) of the income distribution and negatively correlated with income inequality in the top ten percent (99:90 ratio) of the income distribution. A priori, one would expect that areas with higher income inequality also have higher poverty and unemployment. However, this relationship does not hold for the entire distribution. This is evidence that summary measures lose valuable information.

Higher income inequality in the top half (99:90 and 90:50 ratio) of the income distribution is significantly associated with higher economic growth, but the relationship between economic growth and higher inequality in the bottom half (50:10) of the income distribution is not statistically significant. Population growth exhibits the same pattern of relationships as economic growth with the three metrics. People are moving into and business is booming in areas in which there is more inequality at the top of the income distribution. A related measure of well-being, mean income, also shows no significant relationship with income inequality for most of the distribution (50:10, 90:50), but does have a strong, positive relationship with income inequality at the top of the distribution (99:90). This may be an intuitive result as well since average income is necessarily pulled up by increasingly high values at the top of the income distribution.

Finally, skills mix and generational mobility have similar relationships with the three metrics. Skills mix and generational mobility are both significantly negatively correlated with the 90:50 ratio and significantly positively correlated with the 50:10 ratio. This means that higher income inequality in the top half of the income distribution is associated with a less educated and more upwardly mobile population in an MSA, while the opposite is the case for higher income inequality in the bottom half of the income distribution. There is also a negative relationship between generational mobility and the 99:90 ratio, while there is no significant relationship between skills mix and the 99:90 ratio.

In Table 14, the correlations of the three summary income inequality metrics with measures of economic well-being are listed. Unlike Table 13, the results in Table 14 can give an overall sense of the relationship between income inequality and economic well-being.

Table 14: Correlations of Summary Measures with Economic Well-Being: 2014

	Gini	Std. Err.	Theil	Std. Err.	MLD	Std. Err
Economic Growth	0.1482^{+}	0.0508	0.1782^{+}	0.0505	0.0200	0.0514
Population Growth	0.1675^{+}	0.0506	0.1816^{+}	0.0505	0.1223$^{\alpha}$	0.0510
Income Tax Rate	-0.2522^{+}	0.0497	-0.2783^{+}	0.0493	-0.1882^{+}	0.0504
Sales Tax Rate	0.3158^{+}	0.0487	0.2660^{+}	0.0495	0.2393^{+}	0.0499
Cost of Living	0.1605^{+}	0.0507	0.0787	0.0512	-0.0599	0.0513
Total Crime	0.2854^{+}	0.0492	0.2295^{+}	0.0500	0.2891^{+}	0.0492
Poverty	0.4321^{+}	0.0463	0.3855^{+}	0.0474	0.5991^{+}	0.0411
Unemployment	0.1356^{+}	0.0509	0.0802	0.0512	0.1554^{+}	0.0507
Mean Income	0.1378^{+}	0.0509	0.1539^{+}	0.0508	-0.1143$^{\alpha}$	0.0510
Skills Mix	-0.0547	0.0513	-0.0875*	0.0512	-0.0776	0.0512
Generational Mobility	-0.0428	0.0513	-0.0392	0.0513	0.1216$^{\alpha}$	0.0510

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.
Note: $^{+}$ significance at the 1 percent level; $^{\alpha}$ significance at the 5 percent level; * significance at the 10 percent level

According to the three metrics in Table 14, higher income inequality is associated with higher population growth, higher sales tax rates, higher crime, and higher poverty. Two of the three measures are positively and significantly associated with economic growth and unemployment.[12] This means that measures sensitive to the middle and top of the income distribution are correlated with positive economic growth, while a measure which is more sensitive to the lower end of the income distribution has no relationship with growth. In addition, measures sensitive to the middle and lower half of the

[12] The relationship between economic growth and the MLD and the relationship between unemployment and the Theil Index are not statistically significant.

income distribution are correlated with more unemployment, while the measure sensitive to the upper end of the income distribution has no relationship with unemployment.

Higher income inequality is also associated with lower income tax rates in Table 14. This is further evidence of the idea that higher income tax rates reduce inequality or that rich people may be moving to areas with low income tax rates. A more educated workforce (skills mix) is positively and significantly related to lower income inequality using the Theil Index. However, the relationships between skills mix and the Gini Index and the MLD are not statistically significant.

The remaining variables each vary in sign with the metrics in Table 14. More expensive MSAs have higher income inequality according to the Gini index, but there is no significant relationship between cost of living and income inequality according to the other metrics. Similarly, the only significant relationship between income inequality and generational mobility is for the MLD. Higher income inequality using the MLD is associated with less upward mobility. Finally, MSAs with higher income inequality have higher average incomes when using the Gini or the Theil, but have lower average income when using the MLD.

In Table 15, the correlations of the three income distribution-wide ratios with measures of economic well-being are listed. Unlike Tables 13 and 14, which have measures more sensitive or focused on different parts of the income distribution, these measures are interesting because although they are not exactly the same, they are ostensibly measuring nearly the same thing. However, relationships between these metrics and economic well-being still differ.

Table 15: Correlations of Distribution-wide Ratios with Economic Well-being

	Palma	Std. Err.	80:20 Ratio	Std. Err.	90:10 Ratio	Std. Err
Economic Growth	0.1609^{+}	0.0507	-0.0079	0.0514	-0.0020	0.0514
Population Growth	0.1809^{+}	0.0505	0.026	0.0513	0.0758	0.0512
Income Tax Rate	-0.2573^{+}	0.0496	-0.1362^{+}	0.0509	-0.1009*	0.0511
Sales Tax Rate	0.3005^{+}	0.0490	0.3108^{+}	0.0488	0.2300^{+}	0.0500
Cost of Living	0.1310$^{\alpha}$	0.0509	0.1147$^{\alpha}$	0.0510	0.083	0.0512
Total Crime	0.2673^{+}	0.0495	0.3036^{+}	0.0489	0.2198^{+}	0.0501
Poverty	0.4621^{+}	0.0456	0.6279^{+}	0.0400	0.5703^{+}	0.04219
Unemployment	0.1096$^{\alpha}$	0.0511	0.2264^{+}	0.0500	0.1301$^{\alpha}$	0.0509
Mean Income	0.1250$^{\alpha}$	0.0510	-0.0851*	0.0512	-0.0437	0.0513
Skills Mix	-0.0585	0.0513	-0.0194	0.0514	.1196$^{\alpha}$	0.0510
Generational Mobility	-0.0226	0.0514	0.0651	0.0513	0.0872*	0.0512

Source: 2014 American Community Survey. For more information on the ACS, see census.gov/acs.
Note: $^{+}$significance at the 1 percent level; $^{\alpha}$ significance at the 5 percent level; * significance at the 10 percent level

According to the metrics in Table 15, higher income inequality is associated with higher sales tax rates, higher crime, higher poverty, higher unemployment, and lower income tax rates. However, the magnitudes of these correlations vary considerably as some relationships are much stronger than others are.

Higher income inequality is related to higher cost of living according to two of the metrics, but there is no relationship between income inequality and cost of living according to the 90:10 ratio. Higher income inequality using the Palma ratio is related to higher economic growth and higher population growth, but there is no statistically significant relationship between economic growth and population growth and the other two metrics. Finally, higher income inequality is associated with a more educated population when the 90:10 ratio is used, but no significant relationship exists when the other two metrics are used to measure income inequality. Average income is higher in MSAs with higher Gini Indexes, lower in MSAs with higher 80:20 ratios, and has no relationship to the 90:10 ratio.

Table 16 provides a summary of the results of question two. A positive sign means there is a statistically significant positive relationship between the income inequality metric and the measure of economic well-being, a negative sign means there is a statistically significant negative relationship between the income inequality metric and the measure of economic well-being, and a blank means there is no statistically significant relationship between the two variables.

Table 16: Summary of Relationships between Income Inequality and Economic Well-being

	Gini	**Theil**	**MLD**	**Palma**	**80:20**	**90:10**	**50:10**	**90:50**	**99:90**
Economic Growth	+	+		+				+	+
Population Growth	+	+	+	+				+	+
Income Tax Rate	-	-	-	-	-	-		-	-
Sales Tax Rate	+	+	+	+	+	+	+	+	+
Cost of Living	+			+	+			+	+
Total Crime	+	+	+	+	+	+	+	+	
Poverty	+	+	+	+	+	+	+	+	-
Unemployment	+		+	+	+	+		+	-
Mean Income	+	+	-	+	-				+
Skills Mix		-				+	+	-	
Generational Mobility			+			+	+	-	-

Conclusion

The focus of this paper is on how the choice of an income inequality metric affects analysis related to income inequality. Statistically significant and important differences are found between the nine income inequality metrics used in this paper. Therefore, it is possible to get far different views about income inequality in an MSA and in the United States as a whole depending on the income inequality metric used for analysis.

The adjustments made to household income each reduced income inequality. Taxes and transfers reduced income inequality for each metric used, but these reductions were not uniform. These government policies are associated with large decreases in income inequality in the bottom half of the income distribution and smaller decreases in income inequality in the top half of the income distribution. Furthermore, transfers reduced income inequality more than taxes in the bottom half of the income distribution, while taxes reduce income inequality more than transfers in the top half of the income distribution.

Cost of living and equivalence adjustments both reduce income inequality, but the equivalence adjustment has a greater effect than cost of living on income inequality. Equivalence adjustment has a greater effect on the bottom half of the income distribution than on the top half of the income distribution, while the opposite is true for cost of living.

When looking at pair-wise comparison of MSAs, the use of different metrics leads to different conclusions about which MSA has higher inequality. Furthermore, an MSA can have higher income inequality in the lower half of the income distribution and lower inequality in the upper half of the income distribution than another MSA, but this information is lost when a summary measure representing the majority of the income distribution is used.

The relationship between income inequality and measures of economic well-being also vary depending on the choice of income inequality metric. The major takeaway from this area is that the choice of an income inequality metric affects the relationships we see with measures of economic well-being. Not only does the magnitude of these relationships differ, but the direction and the existence of a relationship differs as well.

A positive relationship between economic growth and income inequality is found when income inequality is measured by the 99:90 ratio, the 90:50 ratio, the Gini index, the Theil Index, and the Palma ratio, but no significant relationship between economic growth and income inequality is found when other income inequality metrics are used. Similarly, a positive relationship between population growth and income inequality is found for every metric except the 50:10 ratio, the 90:10 ratio, and the 80:20 ratio. In those cases, no statistically significant relationship exists.

For each income inequality metric except for the 50:10 ratio, there is a negative relationship between income taxes and income inequality and a positive relationship between sales taxes and income inequality. There is also a positive relationship between cost of living and income inequality for metrics other than the Theil Index, the MLD, the 90:10 ratio, and the 50:10 ratio.

Crime and poverty have the same pattern of relationships with income inequality. Each has a positive relationship with income inequality for any metric except the 99:90 ratio. The relationship between the 99:90 ratio and crime is negative for poverty and no statistically significant relationship exists between the 99:90 ratio and crime. There is no significant relationship between income inequality and unemployment when the theil index or the 50:10 ratio are used, a negative relationship when the 99:90 ratio is used, and a positive relationship when any other metric is used to measure income inequality.

For average income, skills mix, and generational mobility, there is either a positive relationship, negative relationship, or no statistically significant relationship with income inequality depending on the metric used.

These results call into question any analysis relying on a single measure of income inequality because it allows researchers to search for the metric that supports a number of conclusions. It suggests that studies involving income inequality should use multiple metrics in their analysis, at least for robustness checks.

Bibliography

Abdullah, Abdul, Hristos Doucouliagos, and Elizabeth Manning. 2015. "Does education Reduce Income Inequality? A Meta-Regression Anaylsis". *Journal Of Economic Surveys* 29(2): 301-316.

Acemoglu, Daron. 1997. "Matching, heterogeneity, and the evolution of income distribution". *Journal of Economic Growth* 2(1): 61-92.

Aghion, Philippe and Peter Howitt. 1998. "Endogenous Growth Theory", MIT Press, Cambridge.

Atkinson, Anthony B. 1970. "On the Measurement of Inequality". *Journal of Economic Theory* 2: 244-263.

Banerjee, A. and Esther Duflo. 2003 "Inequality and Growth: What Can the Data Say?". *Journal of Economic Growth* 8(3): 267-299.

Barro, Robert J. 2000. "Inequality and growth in a panel of countries", *Journal of Economic Growth* 5(1): 5-32.

Bellu, Lorenzo Giovanni and Paolo Liberati. 2006. "Inequality and Axioms for its measurement". *Policy Impacts on Inequality*. Food and Agricultural Organization for the United Nations.

Benabou, Roland. 1996. “Inequality and Growth”. *NBER Macroeconomics Annual* 11: 11-92.

Binatli, Ayla O. 2012. “Growth and Income Inequality: A Comparative Analysis”. *Economics Research International*. 12.

Braun, Denny. 1998. “Multiple Measurements of U.S. Income Inequality”. *Review of Economics & Statistics* 30(3): 398-405.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. “Where is the land of Opportunity: The Geography of Intergenerational Mobility in the United States”. *Quarterly Journal of Economics* 129(4): 1553-1623.

De Maio, Fernando G. 2005. “The Health Effects of Income Inequality in Argentina”. [doctoral thesis] University of Essex.

De Maio, Fernando G. 2007. “Income inequality measures”. *Journal of Epidemiology and Community Health* 61(10): 849-852.

Deininger, Klaus and Lyn Squire. 1996. “A New Data Set Measuring Income Inequality”. *World Bank Economic Review* 10(3): 565-591.

DeNavas-Walt, Carmen and Bernadette D. Proctor. 2015. “Income and Poverty in the United States: 2014”. *Current Population Reports*. U.S. Census Bureau.

Feenberg, Daniel Richard, and Elizabeth Coutts. 1993. “An Introduction to the TAXSIM Model”. *Journal of Policy Analysis and Management* 12(1): 189-194.

Forbes, Kristin. 2000. “A Reassessment of the Relationship between Inequality and Growth”. American Economic Review 90(4): 869-887.

Gastwirth, Joseph. 2014. “Median-based measures of inequality: Reassessing the increase in income Inequality in the U. S. and Sweden”. *Statistical Journal of the IAOS* 30(4): 311-320.

Hasenheit, Marius. 2014. “Inequality: Where Palma is better than Gini”. http://netgreen-project.eu/blog/2014/06/18/inequality-where-palma-better-gini.

Helpman, Elhanan. 2004. “The Mystery of Economic Growth”. Belknap Harvard.

Hisnanick, John J. and Annette L. Rogers. 2007. “Household Income Inequality Measures Based on the ACS Data: 2000-2005”, working paper, U.S. Census Bureau.

Kawachi, Ichiro and Bruce P. Kennedy. 1997. “The relationship of income inequality to mortality: does the choice of indicator matter?”. *Social Science & Medicine* 45(7): 1121-1127.

Krozer, Alice. 2015. "The Inequality We Want: How Much is too Much?". *Journal of International Commerce, Economics, & Policy* 6(3): 1550016-1 – 1550016-27.

Li, Hongyi and Heng-fu Zhou. 1998. "Income Inequality is not harmful for growth: theory and evidence", *Review of Development Economics* 2(3): 318-334.

Litchfield, Julie A. 1999. "Inequality: Methods and Tools". Text for World Bank's Web Site on Inequality, Poverty, and Socio-economic Performance. https://www.researchgate.net/publication/253853150_Inequality_Methods_and_Tools

Palma, Jose Gabriel. 2011. "Homogenous middles vs. heterogenous tails, and the end of the 'Inverted-U': the share of the rich is what it's all about". *Development and Change* 42(1): 87-153.

Perotti, Roberto. 1996. "Growth, income distribution, and democracy: what the data say". *Journal of Economic Growth* 1(2): 149-187.

Persson, Torsten and Guido Tabellini. 1994. "Is inequality harmful for Growth?". *American Economic Review* 84 (3): 600-621.

Shin, Inyong, Hyunho Kim, and Eiji Yamamura. 2009. "Technological Progress and the Future of Kuznets Curve's", MPRA Paper No. 18866.

Shin, Inyong. 2012. "Income Inequality and economic growth", *Economic Modeling* 29 (5): 2049-2057.

Short, Kathleen. 2014. "The Supplemental Poverty Measure: 2013". *Current Population Reports*. U.S. Census Bureau.

Sukiassyan, Grigor. 2007. "Inequality and growth: what does the transition economy data say?". *Journal of Comparative Economics* 35 (1): 35-56.

Tachibanaki, Toshiaki. 2005. "Confronting Income Inequality in Japan – a comparative analysis of causes, consequences, and reform". MIT Press.

Weich Scott, Glyn Lewis, and Stephen P. Jenkins. 2002. "Income inequality and self rated health in Britain". *Journal of Epidemiology and Community Health* 56(6): 436-441.

Weil, David N. 2005. "Economic Growth". Addison-Wesley.

World Bank Institute. 2005. "Introduction to Poverty Analysis". Poverty Manual. http://siteresources.worldbank.org/PGLP/Resources/PovertyManual.pdf