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Measuring Income Inequality in Farm States: Weaknesses of the Gini Coefficient

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EXECUTIVE SUMMARY

Income inequality has become a major issue as the gap between the poor and rich continues to increase within the United States. General interest has led to academic studies from a variety of fields, such as psychology and economics. These studies conclude that income inequality results from factors such as education, an aging labor force, and the geographic distribution of populations. Much attention has been directed toward determining why income inequality exists and its effects on society. However, little research has been done on the validity of the methods used to measure income inequality.

This paper focuses on the Gini coefficient, the primary method used to measure income inequality. The paper questions its validity because the measure uses inconsistent data as its main input. Farm income, which is difficult to compare accurately with other types of income, is used to evaluate the validity measure. Using the five states with the largest farm sectors, the paper analyzes the relationship between the Gini coefficient and such commonly cited factors behind inequality.

The existence of a large proportion of farm income as a percentage of total income in a state altered the estimated Gini coefficient for four of the five states analyzed. A higher concentration of farm income produces a less consistent Gini coefficient result, one that is not comparable to other states. This result reduces confidence in the usefulness of the Gini coefficient when measuring income inequality for states with large farm sectors. Further, it calls into question the reliability of the index itself.

INTRODUCTION

In the last few years, income inequality has been widely debated. It has worked its way into almost all political discussions and will undoubtedly be discussed during the presidential debates. Income inequality is most commonly measured using the Gini coefficient, which was developed in 1912 by Italian social scientist Corrado Gini. It measures discrepancies in income as a percentage of a whole, where one equals complete income inequality (a score of one indicates that a single individual has all of the income and everyone else has none; a score of zero indicates income is distributed equally among all people).

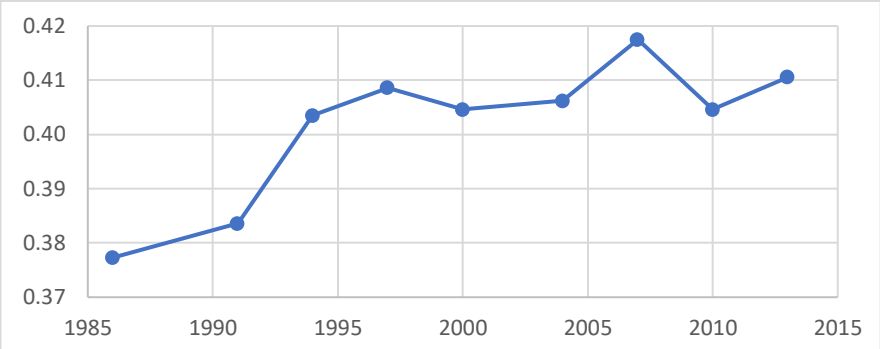
The Gini coefficient relies heavily on measurements and definitions of income. The equation's main input is, of course, income. However, measurements of income are subject to many discrepancies including tax credits, depreciation of capital assets, and subsidies. It is almost impossible to determine how best to measure income in the United States. Certain basic principles apply to everyone filing tax returns, but researchers make many exceptions in accordance with their accounting methods and their differential treatment of different types of income-earning activities. Such differences in how countries or states measure income can massively skew the data.

Income for various industries is often even incomparable. For this reason, the focus of my paper is on income inequality, as reflected in the Gini coefficient, in states with the highest farm income as a percentage of total income. Farm income is particularly hard to standardize because of the extent of tax credits and subsidies in the industry. Farmers also often invest in large capital assets that amortize over time, creating an illusion of lost revenue. Often farmers have to reinvest their revenue into their land and equipment to keep their businesses going. Accounting methods consider reinvestment as a business expense and do not include it in the measurement of income. This method might be good for measuring farm income; however, it is not very helpful for comparing farm income with income in other industries.

Five states with the highest farm income as a percentage of total income (South Dakota, Nebraska, Iowa, North Dakota, and Idaho) were used to determine whether the differences in income-data collection methods significantly impacted the Gini coefficients for these states. I compared farm income to total income to determine whether the Gini coefficient is meaningful when calculated using farming income. In the measurement of farm income, crop farming and ranching were included.

In *Earnings from Inequality and Mobility in the United States: Evidence from Social Security Data since 1937,* Kopcuk claims that since 1953, income inequality, as measured by the Gini coefficient, has risen sharply in the United States. In the past five years, income inequality has risen more gradually across the country. Figure 1 illustrates that the United States' Gini coefficient has risen from 0.378 in 1986 to 0.411 in 2013. Many studies have attempted to discover the factors that have caused US inequality and its resulting consequences. There has been less analysis on the methodologies used in measuring inequality.

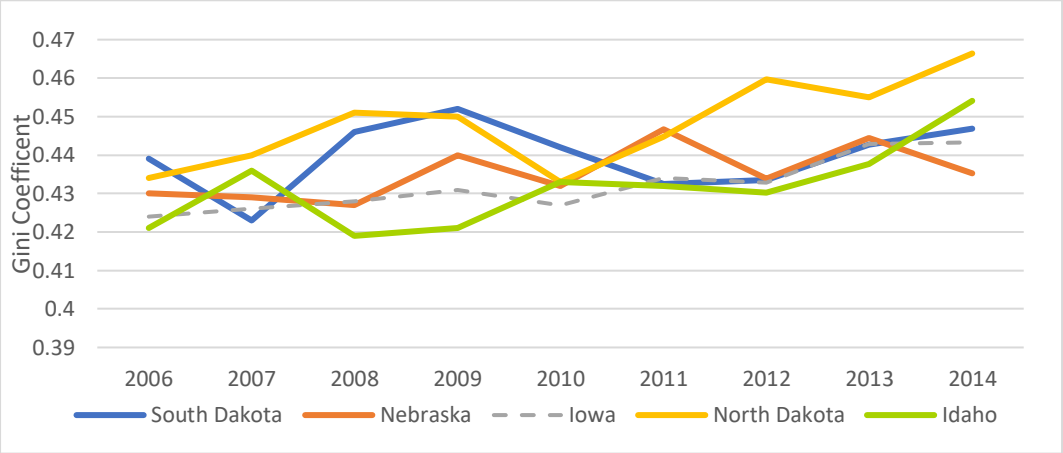
Figure 1: US Gini coefficient, 1986-2013



Source: World Bank

Figure 2 demonstrates each of the five high farm income states' Gini coefficients in recent years. Notice the large increases and decreases on the state level and how different states are affected by economic changes throughout the years to varying degrees. The model begins with South Dakota because it has the highest farm-income percentage and ends with Idaho as it has the lowest share of farm income out of the five states.

Figure 2: Increase in Gini index in farm states, 2006-14



Source: US Census Bureau

BACKGROUND

Academics have written on income inequality since the mid-twentieth century, focusing on varying aspects and reaching varying conclusions. Some have chosen to focus on psychological and social effects of income inequality, and others have looked for the underlying causes with economic models.

Many scholars, such as Lisa Berkman (2014), take a psychological approach, searching for the consequences of the massive amount of inequality on personal well-being. Research conducted by Michael Norton (2011) showed that Americans tend to underestimate income inequality. Citizens think the income of the richest members of society and the poorest members of society are closer than they actually are. These scholars have proven that income inequality affects psychology, but this paper focuses on economic concerns.

The Gini coefficient is derived from the estimated difference between the slopes along the Lorenz curve. This can cause mathematical errors when negative incomes are included. Scholars such as Joseph Gastwirth (1972) are willing to admit the results are skewed: "the method used by the Census Bureau often leads to estimates which are outside of mathematically possible bounds." But very few call into question the data-collection methods as problems in and of themselves. Perhaps the most important agreement of these works is that the Gini index measures relative inequality.

Popular modern theories focus less on the actual equation Gini created and more on the reasons why inequality is increasing as measured by the Gini coefficient. These studies start with different assumptions, making comparisons difficult. Despite the varied theories about what factors influence income inequality the most, it is clear income inequality is rising in the United States. According to Janet Yellen (chair of the Board of Governors of the Federal Reserve), the top 10 percent of American incomes increased by about 30 percent since 1973. The bottom 50 percent of workers' real income only rose by about 5 percent. Researchers tend to conclude that income inequality is exacerbated by differences in education, an aging labor force, and the concentration of populations.

My research argues that concentration of income within a state should be considered when evaluating the effectiveness of the Gini coefficient. When an industry deviates from the normal income tax structure, it may have an effect. I seek to show that a high concentration of farm income decreases the Gini coefficient.

THEORY AND DATA DESCRIPTION

To compute Gini coefficients, one must rely on tax data from federal and state income tax reports. I collected the Gini coefficients for the counties of each of the five states from the Census Bureau's 2013 dataset. Farm data measuring 2013 incomes comes from the Bureau of Economic Analysis. Farm income here includes both incomes generated from the cultivation of crops and cattle ranching. However, a difficulty arises because most farmers' wealth is not measured using the traditional income tax model.

Compared to other producers, farmers have more of their wealth invested in capital assets such as expensive mechanical implements and land. In addition, a lot of farm expenses and tax deductions offset profits and thus taxable income. This poses a problem for the Gini coefficient's reliability for farms because income is the main input for deriving it. In fact, the Department of Agriculture, in its statistics on farm income and wealth, does not measure the success of farms in terms of their income, but rather their wealth. To measure wealth, they use cash receipts and ownership of capital. This has such a large effect on the data that it actually changes the ranking of which states profit the most from farming, meaning that the department's method implies that just because certain states have the highest reported farm income does not mean they benefit the most from farming.

For South Dakota, Nebraska, Iowa, North Dakota, and Idaho, I compared the income inequality of individual counties to the average of the other counties within the state and determined possible factors that could cause Gini index discrepancies. Then I aggregated this information to compose a state profile by arranging the counties into five quintiles, with quintile one containing the counties with the lowest Gini coefficient, suggesting the lowest income

inequality, and quintile five containing the counties with the highest Gini coefficient, suggesting the highest income inequality.

Observations collected on commonly cited factors for income inequality include education (measured by the percentage of the population with a high school degree or higher), median age, and population density. County data was averaged counties in each quintile to more easily see the relationship between the Gini coefficient and each factor. Then the impact farm income as a percentage of total income has on the Gini coefficient is reported. The states were then compared on the same basis.

DATA ANALYSIS

I further examined the information described above by using regression correlation analysis. Table 1 demonstrates how the commonly evaluated factors relate to the Gini coefficient in each state. It shows that all of the factors have a low impact on the Gini coefficient. Notice the wide variations. This demonstrates that the cited factors are not as relevant as researchers tend to believe and that they do not fully carry over across state lines. The results of regression analysis are displayed in Tables 2–4.

Table 1: Correlation of factors to the Gini coefficient by state

	Correlation Coefficient				
Factor	**South Dakota**	**Nebraska**	**Iowa**	**North Dakota**	**Idaho**
Farm income as % of total income	0.10	0.26	-0.07	-0.06	-0.31
Median age	-0.07	0.05	-0.08	-0.11	0.17
High school degree or higher	0.11	0.02	-0.34	0.13	-0.32
Population density	-0.14	-0.18	0.19	-0.08	0.13

Further regression analysis led to a deeper understanding of the relationships between these factors. Table 4 highlights the results. Working with five states and five sets of data required a thorough, multi-test approach. Using Idaho as the base state, farm income as a share of total income in relation to the Gini index was analyzed across the states. This approach produced initially puzzling results. Farm income as a percentage of total income when compared on a county level showed a significantly positive relationship, meaning as farm income as a percentage of total income increased so did the Gini coefficient for that area, as shown in Table 4.

Table 2: Variable explanations for regression results

Variable Name	Description of Variable
Farm income as % of total income	Farm income as a percentage of the total income for all counties
Median age	Median age of the population for all counties
Educational attainment	Percentage of the population with a high school or higher educational degree for all counties
Population density	Amount of people per square mile for all counties
Nebraska	The difference in the relationship between Nebraska's Gini coefficient and farm income as a percentage of total income and Idaho's
South Dakota	The difference in the relationship between South Dakota's Gini coefficient and farm income as a percentage of total income and Idaho's
Iowa	The difference in the relationship between Iowa's Gini coefficient and farm income as a percentage of total income and Idaho's
North Dakota	The difference in the relationship between North Dakota's Gini coefficient and farm income as a percentage of total income and Idaho's
INE	Nebraska's farm income as a percentage of total income times the indicator variable
ISD	South Dakota's farm income as a percentage of total income times the indicator variable
IIA	Iowa's farm income as a percentage of total income times the indicator variable
IND	North Dakota's farm income as a percentage of total income times the indicator variable

Then the states were evaluated and compared individually. As expected, South Dakota and Nebraska both demonstrated that as farm income as a share of total income increased among counties, so did the Gini coefficients. The opposite was true of Idaho. It presented a negative relationship between farm income as a share of total income and the Gini coefficient, meaning as farm income as a share of total income increased, the Gini coefficient decreased. North Dakota and Idaho both showed negative relationships between farm incomes and Gini coefficients, but the results were not statistically significant. Table 3 demonstrates the net impact of farm income as a percentage of total income on each state's Gini coefficient.

Table 3: Summary of the effects of the Gini index

State	Effect of the Gini Coefficient	Average Farm Income as a Percentage of Whole Income	Net Impact
Nebraska	0.0716	23.4504%	1.6795%
South Dakota	0.0393	21.2396%	0.8345%
Iowa	-0.0100	13.0175%	-0.1297%
North Dakota	-0.0132	15.0718%	-0.1989%
Idaho	-0.0971	9.7126%	-0.9436

Table 4: Regression analysis

Summary Output	
Regression Statistics	
Multiple R	0.4278
R-squared	0.1830
Adjusted R-squared	0.1543
Standard error	0.0315
Observations	355

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	12	0.0762	0.0063	6.3828	3.06199E-10
Residual	342	0.3402	0.0010		
Total	354	0.4164			

	Coefficients	*Standard Error*	*t stat*	*P-value*
Idaho (used for comparison)	0.4465	0.0159	28.0616	0.0000
Farm income as share of total income	-0.0971	0.0445	-2.1838	0.0297
Median age	-0.0001	0.0003	-0.3169	0.7515
Educational attainment	-0.0566	0.0353	-1.6002	0.1105
Population density	0.0000	0.0000	-0.2753	0.7832
Nebraska	-0.0163	0.0093	-1.7510	0.0808
South Dakota	0.0130	0.0097	1.3473	0.1788
Iowa	-0.0020	0.0090	-0.2227	0.8239
North Dakota	0.0277	0.0097	2.8617	0.0045
INE	0.1688	0.0518	3.2550	0.0012
ISD	0.1364	0.0533	2.5583	0.0109
IIA	0.0872	0.0612	1.4234	0.1555
IND	0.0872	0.0612	1.3752	0.1700

CONCLUSION

These data show that farm income has an impact on the Gini coefficient in four of the five states tested. If the Gini coefficient was an exact measure, the strong presence of a certain industry should not sway results. Thus, this study undermines the usefulness of the Gini coefficient for measuring income inequality for states heavily dependent upon farm income.

This inaccuracy has implications when considering differences in tracking income inequality. The presence of the farming industry alters the reliability of the Gini coefficient in measuring income inequality. Income inequality also relies on consistent income data, which is not usually available. Farm income is not the only distinctively measured form of income, which suggests that states that have other concentrations of industries could potentially produce skewed Gini coefficient measures as well. This means comparing county inequality is not very useful when the data and income are computed differently.

In a time when income inequality is such a highly controversial issue, it is important for policy makers and the public to understand that the measures used to describe income inequality are flawed. Following a flawed system to reach important decisions leads to flawed decisions. To reach more accurate decisions, economists, policy makers, and the public need to consider alternative ways of evaluating income inequality.

The existence of a relationship between farm income and the Gini coefficient should motivate further investigation. Perhaps this difference is caused by the inclusion of both crop cultivation and cattle ranching in farm-income measurements. This inquiry should be further tested in future research.

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