Measuring Income Inequality in Farm States: Gini Coefficient Weakness

Abstract

As the gap between the highest and lowest incomes increases rapidly in the United States, voters, politicians and researchers have become more aware of the importance of this difference. General interest has sparked academic studies of the issue in many fields of expertise such as psychology and economics. These researchers, in general, conclude that income inequality emanates from education gaps and other demographic and economic characteristics. Researchers have directed much less attention to examining the tools used to measure income inequality. The present research focuses on the primary measure used to gauge income inequality, the Gini Index, questioning its validity in states with a high share of income coming from agriculture. Investigating the five U.S. states with the largest ratios of farm to non-farm income for the years 2010-2014, the study concludes that the existence of a high proportion of farm income statistically altered the estimated Gini coefficient for all of the five states examined. Results thus undermine the usefulness of the Gini index in measuring income inequality for states with large farm sectors.

Keywords: Gini Coefficients, Income Inequality, Farm Income

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Introduction

Over the past several years and in recent election debates, income inequality has become a widely argued topic of public interest. Furthermore, it has been broadly accepted that U.S. income inequality has increased dramatically over the past several decades. Researchers typically use the Gini Index to measure income inequality among states and nations. The index, developed in 1912, measures the distribution of income with a score ranging between zero (complete equality), where income is evenly divided among all, and one (complete inequality), to one where a single individual has all of the income, and everyone else has none.

As expected, the Gini Coefficient relies heavily on the definition of income. However, measurements of income are subject to many discrepancies including tax credits, exclusion of capital assets, and subsidies. Since the definition of income varies significantly, the value of the Gini Coefficient will depend heavily on the definition. For example, in terms of filing federal tax returns, many exclusions and exemptions are made according to the individual taxpayer situation that renders income comparisons less meaningful. Thus, differences in measuring income among the U.S. states can lead to skewed data with potentially questionable measures of income inequality.

Income derived from certain industries can further reduce comparability. For example, farm income is not comparable to non-farm income for a variety of reasons. In 2014, federal support payments represented 8.7 percent of total farm earnings. Moreover, government payments are not evenly distributed because they go only to farms producing certain agriculture commodities, and the largest farms have historically received a disproportionate share of the payments (Edwards, 2005 and 2016). The effect on income distribution, then, is to disproportionately increase the incomes of the top 20 percent of farm households by up to twice the amount of the middle 60 percent of households (USDA, 2012).[1]

Farm income also does not compare well with nonfarm income due to the extent to which farmers make greater use of tax credits than nonfarm households and nonfarm enterprises. Farmers also often invest in large capital assets that amortize or depreciate over

[1] **http://www.ers.usda.gov/media/889402/aer812g.pdf. Accessed May 25, 2016.**

time. To the extent that the actual depreciation charges do not match the actual decline in value, farm income is mis-measured in comparison to the taxable entities with little depreciable assets. Futhermore, the USDA determined that on average, farms reduced before-tax household income by more than 25 percent to compensate for farm business losses. In contrast, only four percent of nonfarm businesses incurred losses that reduced before-tax household income (USDA, 2012, p. 34).

Due to these differences, it is hypothesized by the present study that the existence of a high share state income generated by the farm sector alters the effectiveness of the Gini Coefficient in comparing income inequality among U.S. states and political subdivisions. It is hypothesized that this poses a problem for the Gini Coefficient's reliability for comparing income inequality for a farm state to a non-farm state. In fact, the USDA in its "*Farm Income and Wealth Statistics"* does not measure the success of farming in America in terms their income, but rather their wealth. To reach this number, they use cash receipts and ownership of capital from each state.

The present study will focus empirical tests on the five states with the highest 2013 farm income as a percentage of total income. The states in terms of the highest share of income produced by the farm sector in descending order for 2013 were: [2] South Dakota, Nebraska, Iowa, North Dakota, and Idaho.[3]

Rising Income Inequality

Kopcuk (2010) claims that since 1953, income inequality, as measured by the Gini Coefficient, has risen sharply in the United States. However, in the past five years, income inequality has climbed more gradually across the country. Figure 1 illustrates this shift in income distribution from 1986 to 2013. The United States Gini Coefficient has risen from 1986 (0.378) to the year 2013 (0.411) with higher Gini Coefficients representing greater income inequality.

Figure 2 profiles the Gini Coefficient of each of the five comparison states from 2006 to 2014. Note that all five states experienced an increase in the Gini Coefficient, signifying greater income inequality, over the time period. How much influence did the share of income derived

[2]In 2014, South Dakota surpassed Nebraska in the share of total income derived from farming. Throughout this study, farm income includes income from crop and animal production.

[3]Except for Idaho, each of these five states is located in the West North Central U.S. Census region thus other important factors influencing the Gini coefficient are, to a degree, reduced (e.g. racial differences).

from farming influence the Gini Indices or Coefficients? For example, between 2006 and 2014, farm personal income rose by 151.9 percent while non-farm personal income climbed by a much smaller 24.7 percent. The question posed by this study is, did this growth differential reduce the ability of the Gini Coefficient to make inter-state comparisons regarding the trend in income inequality?

Past Research

Principally, since the mid-twentieth century researchers from multi-disciplines investigated income inequality focusing on varying aspects and reaching wide-ranging conclusions. Few scholars have focused on the impact of farm income on the Gini Coefficient, while many scholars have focused on psychological and social effects on income inequality while others investigated the underlying factors influencing income inequality as captured by the Gini Coefficient.

Scholars, such as Berkman (2014), chose to take a psychological approach, searching for the consequences of the mass amount of inequality on personal well-being. Research conducted by Norton (2011) showed that Americans tend to underestimate income inequality. According to Norton, citizens think that the income of the richest members of society and the poorest members of society are closer than they actually are.

Other studies have focused on the calculation of the index. The Gini Coefficient is the result of the estimated difference between the slopes along the Lorenz Curve. This can cause mathematical errors from the inclusion of negative incomes. Economists have tried to correct for these errors by using revised statistical models that limit different aspects of the formula.

Popular modern theories focus less on the actual Gini formula and more on the reasons why inequality is increasing according to his equation. These studies start with different assumptions, which makes comparisons less meaningful. Despite their varied theories about what factors influence it the most, it is clear that income inequality is rising in the United States. According to Janet Yellen (2006), Chair of the Board of Governors of the Federal Reserve, concluded that since 1973 the top 10 percent of American incomes increased by about 30 percent while the bottom 50 percent of workers' real income rose only by about 5 percent. Many studies have attempted to determine why this is happening.

Researchers tend to conclude that income inequality is exacerbated by gaps in education (Muller, 2002), an aging labor force (Drosdowski, et al., 2015), and the presence of concentrated or more densely populated areas (Glaesar, 2009). This research argues that many factors can also be added to this list of things that affect the Gini Coefficient. Any industry that deviates from the normal income tax structure is subject to having an effect on the index. The present study examines the impact of high concentrations of farm income on the Gini Coefficient. Does the fact that farm income growth has massively exceeded that of non-farm income expansion over the past five years render the Gini Coefficient less useful in comparing income inequality?

Small business owners have a different tax structure and the ways they compute their taxes will have a different effect on the Gini Coefficient compared to normal wages. Sole proprietorships and other self-owned businesses will often make large use of tax deductions. Like farmers, small business owners use section 179 for tax deductions. Individuals who own small businesses can lease, finance, or purchase new or used equipment with limits for this writes of up to $500,000 in a single year. Section 179 allows those who qualify for this tax deduction to write off the full value of the vehicle the year it is released among other plans that created tax deductions for the depreciations of new vehicles (Integrity Financial Groups, LLC 2016). The different tax structure and larger use of small business owners can have a similar effect on the Gini Coefficient as farm income.

One group of people whose income levels are affecting poverty rates and possibly the Gini Coefficient are college students. Alemayehu Bishaw (2013) found that 51.8 percent of college students living off-campus and not with relatives had income below the poverty line, and once these incomes were removed, the U.S. poverty rate dropped from 15.2 percent to 14.5 percent. While individuals will go to school to increase their future earnings, they cannot work much while they are in school and often work low paying jobs, which in turn make their income lower. Incorrect decisions may be made from the poverty level as the college income levels make it appear lower than it would otherwise be. College students temporarily lower income levels could distort the Gini Coefficent in the same manner, but instead making it appear higher than it should be.

Scholars such as Gastwirth (1972, p. 2016) admit that the Gini Coefficient is artificially skewed, “the method used by the Census Bureau often leads to estimates which are outside of mathematically possible bounds.” However, few researchers call into question the industry source of income. That is, how encompassing is the income data? Does it account for industry differences whereby certain income may go uncounted or double-counted? Perhaps the most important agreement of these works is that the Gini Coefficient measures "relative inequality." This makes the debate of data collection more important than before because this relies on consistent data collection even more.

Little research has been done on the effect of farm income on the Gini Coefficient, but El-Osta and Gilespie (2009) examined the role of government payments to households with farm income. The study conducted for the different farming regions of the U.S. and the years 1996-2001, concluded that government support payments did account for variations in the Gini Coefficient and that with higher government payments, the Gini Coefficient would be lower than it would be otherwise due to inflated wealth (Mishra, El-Osta, and Gillespie, 2009).[4]

Income inequality has also been found to be greater in farm households compared to nonfarm households. For example in 2001, the bottom 60 percent of farm households only had 23.3 percent of total farm income. It was also concluded that government payments correlated moderately with total income (Mishra et. al. 2002). It should be noted these studies examining the relationship between farm income and income inequality were conducted when the FAIR Act[5] was in place. Since then, there has been a new Act put in place that had the impact of lowering government support payments for agriculture.

The most recent bill affecting farm income is the *Food, Conservation, and Energy Act* of 2008. Limits of payments were set to $40,000, $65,000, and $75,000 per entity depending on the program type, among other limitations to specific types of farming such as cotton farming and dairy farming, which is argued to hurt the farm industry (Harris et. al. 2008). Given this change, it is important to investigate how the change affected the Gini Coefficient. Before this change, there were not such tight caps on government support payments, meaning that they often made the Gini Coefficient higher than otherwise due to the concentration of support payments among larger and higher income farms. It is hypothesized that these caps put in place from that farm bill had the impact of reducing income inequality among farm operations.

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[4] Note that these payments do not include disaster relief payments.

[5]Federal Activities Inventory Reform Act of 1998 (FAIR). An act to provide a process for identifying the functions of the Federal Government that are not inherently governmental functions, and for other purposes. <<NOTE: Oct. 19, 1998 - [S. 314]>>. Be it enacted by the Senate and House of Representatives of the United States of America in Congress assembled, <<NOTE: Federal Activities Inventory Reform Act of 1998. 31 USC 501 note.>>

Certain types of farming receive more government support payments than others with livestock farmers generally excluded from receiving support payments. Given these changes and the importance of farm income to some states, it is the objective of this study to examine the relationship between the Gini Coefficient and farm income using more recent data.

Data Description and Methodology

The Gini Coefficients for the counties of each of the five states were collected from the U.S. Census Bureau for 2010-2014. Data on 2010-2014 farm and non-farm income come from the U.S. Bureau of Economic Analysis. Farm income here is the total reported income from farmers by county in the five states. County income was used to calculate Gini Coefficients for each of the 355 counties for five years in the five farming states; South Dakota, Nebraska, Iowa, North Dakota, and Idaho. The counties were placed into quintiles based on Gini Coefficients from lowest income inequality, Quintile 1, to highest income inequality, Quintile 5. Factors that past research has concluded as influencing income inequality were calculated by county. These included education, measured by the percent of the population with a high school degree or higher, median age, percent of births to unmarried mothers, percent white, and population density.

Table 1 lists the average values for variables associated with income inequality in previous studies for the 355 counties ranked by Gini Coefficients for 2014. As listed Quintile 1, which has the lowest average Gini score, or least income inequality, as expected, has the highest percent of the population that is high school graduates, the least percent of births to unmarried mothers, the highest percent white population, and lowest average age.

Quintile 5, counties with the greatest income inequality, are the least densely populated, have the second lowest average age, the lowest percent white population, highest percent birth to unmarried mothers, and have the second lowest percentage of high school graduates. Central to the present study, data in Table 1 indicate that counties experiencing the greatest degree of income inequality as measured by the Gini Coefficient, Quintile 5, had the highest farm income as a share of total county income for 2014.

Table 2 contains additional descriptive statistics for the counties in the five farm states. Date show that North Dakota and South Dakota have the highest share of their counties in Quintile 5, or counties with the greatest degree of income inequality. These same two states had the smallest proportion of their counties in Quintile 1, or counties with the least degree of income inequality. Likewise, these two states had the largest percentages of farm income to total income.

Table 3 lists correlation coefficients between Gini Coefficients and factors expected to influence the Gini Coefficient. It shows that all of the factors researched in this study are relatively unrelated to the Gini Coefficient. Note the wide variations of correlations between the data. This demonstrates that, the factors are not as related in a univariate sense as researchers tend to hypothesize, as least for the five farm dominated states.

Further analysis using multiple regression leads to a deeper understanding of the relationship between the independent factors in Table 3 and the county's Gini coefficient. Equation (1), the base model, (2) and (3) will be estimated:

$$\text{Gini coefficient} = \beta_0 + \beta_1\,\text{FarmIncRatio} + \beta_2\,\text{Age} + \beta_3\,\text{HighSchool} + \beta_4\,\text{PopDensity} + \beta_5\,\text{PercentWhite} + \beta_6\,\text{PercentBirth} + \beta_7\,\text{YR2011} + B_8\,\text{YR2012} + \beta_9\,\text{YR2013} + \beta_{10}\,\text{YR2014} \quad \text{(Equation 1) base model}$$

$$\text{Gini coefficient} = \beta_0 + \beta_1\,\text{FarmIncRatio} + \beta_2\,\text{Age} + \beta_3\,\text{HighSchool} + \beta_4\,\text{PopDensity} + \beta_5\,\text{PercentWhite} + \beta_6\,\text{PercentBirth} + \beta_7\,\text{YR2011} + B_8\text{YR2012} + \beta_9\text{YR2013} + \beta_{10}\,\text{R2014} + \beta_{11}\text{IA} + \beta_{12}\text{ND} + \beta_8\text{NE} + \beta_9\,\text{SD} \quad \text{(Equation 2)}$$

$$\text{Gini coefficient} = \beta_0 + \beta_1\,\text{FarmIncRatio} + \beta_2\,\text{Age} + \beta_3\,\text{HighSchool} + \beta_4\,\text{PopDensity} + \beta_5\,\text{PercentWhite} + \beta_6\,\text{PercentBirth} + \beta_7\text{YR2011} + B_8\,\text{YR2012} + \beta_9\text{YR2013} + \beta_{10}\text{YR2014} + \beta_{11}\text{IA} + \beta_{12}\text{ND} + \beta_{13}\text{NE} + \beta_{14}\text{SD} + \beta_{15}\text{IIA} + \beta_{16}\text{IND} + \beta_{17}\text{ISD} + \beta_{18}\text{IND} \quad \text{(Equation 3)}$$ [6]

Table 4 provides definitions of the variables listed in Equations (1), (2) and (3). Using Idaho as the base state, the impact of farm income as a share of total income on county Gini Coefficients across states is estimated. A fixed effects model was used instead of an OLS regression to account for the variation of error terms and variation in the Gini Coefficient over the years that was not otherwise captured by the independent variables.

[6] A fixed affects model was used to account for the varying error terms in the years that could account for other things affecting the Gini Coefficient.

Estimates of Equation (1), the base model, are listed in Table 5. As listed, the ratio of farm income to personal income does not have a statistically significant impact on county Gini Coefficients. Estimation also indicates that increases in average age and population density increase income inequality. On the other hand, increases in the percent of the population that is white reduces income inequality as proxied by the Gini Coefficient.

Also listed in Table 5 is the estimation of Equation (2). All of the control variables have the same impact on the dependent variable and the variable of interest is again not statistically significant. Estimation of Equation (2) also indicates that counties in Iowa, North Dakota and South Dakota have higher Gini Coefficients, other factors constant.

Next Equation (3) is estimated to determine if the relationship between farm income and income inequality differs by state and is presented in Table 6. As presented, for counties within Iowa, Nebraska, North Dakota and South Dakota, as farm income as a share of total income increased, so did their Gini Coefficients. The opposite was true of Idaho. It exhibited 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 increases, the Gini Coefficient decreases, or county income inequality declines.

What accounts for this difference by state? Some of this variation between states may emanate from government payments. Figure 3 shows government support payments per $1,000 of farm income. In 2014, Idaho had the lowest amount of government payments as a percent of farm income while Iowa had the highest amount, which may lead to varying distortion of income inequality. Also note how North Dakota’s government support payments decreased over the years.

In order to investigate the relationship between the Gini Coefficient and farm income, Equations (1) and (2) are re-estimated substituting government farm support payments for farm income in each estimation. Empirical results are presented in Table 8. As indicated, government farm support payments have a statistically significant and negative impact on income inequality, as measured by the Gini Coefficient for both Equation (1) and (2).

As discussed earlier, from 1996 to 2001 the federal government placed relatively loose caps on government support payments, with large and potentially wealthier farms receiving a disproportionate share of these payments. This likely contributed to growing income inequality among counties using the Gini Coefficient as a gauge. Once payments were more significantly capitated, the payments appear to have actually reduced income inequality between 2010 and 2014.

As farmers receive government support payments their income rises and with the caps on amounts of government support payments now included in farm bills, smaller and lower revenue farm began to receive a larger share of government support payments. Results contained in Table 8 support the hypothesis that these payments reduced county income inequality as measured by the Gini Coefficient. However, this is a topic that will be addressed in a future paper. But data presented in Table 7 show that the two states with highest government support payments as a percentage of farm income, North Dakota and South Dakota, also have the highest Gini Coefficients.

These seemingly contradictory findings merit a deeper investigation in a future study. Some of the explanation may be the result of the distribution by county in farm size. According to the 2012 Census of Agricultural, 97 percent of American farms are family owned and fewer than 9 percent of farms were midsize, large, and very large sized farms. The gross cash farm incomes (GCFI) for midsize, large and very large farms were, respectively $350,000 to $999,999, $1 million to $4.9 million, and $5 million or more. Furthermore, midsize farms accounted for 26 percent of net farm income while large and very large farms accounted for 56 percent of net farm income.

Large and very large farms predominate in four of the five states in this study and are listed in order by percent of large and very large farms combined: North Dakota (11 percent), Nebraska (8 percent), South Dakota (7 percent), and Iowa (7 percent). (USDA, 2012). If only a small percentage of farms are earning over half of net farm income, there is high income inequality for farm income households. It may be that reductions in farm income, which hits all farms, produces higher government support payments which are disproportionally received by smaller farms. However, this possibility must be more fully examined in a future study.

This study concludes that farm income distorts the Gini Coefficient and further finds that government farm support payments mitigate that impact. However, the large proportion of government support payments do not seem to be improving the income inequality within North Dakota and South Dakota, who have the highest Gini Coefficients and in the results from Table 6, appear to have the largest increase in the Gini Coefficient from an increase in farm income. There is another variable at work here not covered by this study and should be further examined in a subsequent study.

Conclusion:

This study has demonstrated that farm income has a statistically significant impact on the Gini Coefficient for the five states that were examined. Thus the present analysis undermines the use of the Gini Coefficient as a comparison measure of income inequality among areas that differ significantly in terms of the relative size of the farm sector.

However, that impact appears to be reduced by government farm support payments. This has large implications when considering differences in tracking income inequality. This variable sways the outcome of the most common measure of income inequality. Income inequality relies on consistent income data, which is not usually available.

In a time where income inequality is such a highly contested issue, it is important for policy-makers and the public to understand that the measures used to describe income inequality are influenced by factors such as the relative size of the county and state farm sector. To reach more relevant decisions economists, policy-makers, and the public need to consider alternatives ways of adjusting the income inequality measures to account for factors such as farm income.

References

"Agriculture." *Agriculture*. United States Environmental Protection Agency, 1 Oct. 2015. Web. 12. April. 2016.

Bee, Adam. "Household Income Inequality Within U.S. Counties: 2006–2010." *American Community Survey Briefs* (2012). *Censusbureau.gov*. United States Department of Commerce. Web.

Berkman, Lisa, S.V. Subramanian, and Ichiro Kawachi. "Income Inequality." *Social Epidemiology*. Oxford UP, 2014. 126-152. Print.

Bishaw, Alemayehu. "Examining the Effect of Off-Campus College Students on Poverty Rates." *U. S. Census Bureau, Social, Economic & Housing Statistics Division, Poverty Statistics Branch* (2013): 5. Web. 28 Jan. 2017.

Deal, Melanie. "American Indian and Alaska Native Poverty Rate About 50 Percent in Rapid City, S.D., and About 30 Percent in Five Other Cities, Census Bureau Reports." *U.S. Census Bureau* (2013): n. pag. Web. 2 Feb. 2017.

Drosdowski, Thomas, Britta Stover, and Marc Ingo Wolter, "The Impact of Aging on Income Inequality, GWS, 2015: pp. 1-18.

Edward, Chris, "Downsizing the Federal Government," The Cato Institute, Washington, DC, 2005.

Farm Income and Wealth Statistics." *United States Department of Agriculture: Economic Research Service*. United States Department of Agriculture. Web.

Gastwirth, Joseph L.. "The Estimation of the Lorenz Curve and Gini Index". *The Review of Economics and Statistics* 54.3 (1972): 306–316. Web.

Glaesar, Edward, Matt Resseger and Kristina Tobio, "Inequality in Cities," Journal of Regional Science, 49:4, 2009, pp. 617-46.

"GINI Index (World Bank Estimate)." *GINI Index (World Bank Estimate)*. World Bank, Development Research Group, 2015. Web. 12. April. 2016.

Harris, Web, Brad Lubben, James Novak, and Larry Sanders. "The Food, Conservation, and Energy Act of 2008 Summary and Possible Consequences." *The National Farm Bill Train the Trainer Conference* (2008): n. pag. Web. 13 Nov. 2016.

Integrity Financial Groups, LLC. "Why Companies Should Take Advantage of Section 179 Year-End Deductions for Equipment Financing Explained by Integrity Financial Groups, LLC." *Why Companies Should Take Advantage of Section 179 Year-End Deductions for Equipment Financing*. LexisNexis Academy , 14 Nov. 2016. Web. 29 Jan. 2017.

Kopczuk, Wojciech, Emmanuel Saez, and Jae Song. "Earnings Inequality and Mobility in the United States: Evidence from Social Security Data since 1937 *." *Quarterly Journal of Economics* (2010): 91-128. Print.

Janssen, Larry and Hamda, Yonas, "Distribution of Farm Program Payments in South Dakota" (2007). Economics Commentator. Paper 477.

Mishra, A.K., El-Osta, H.S. M.J. Morehart, J.D. Johnson, and J.W. Hopkins. "Income, Wealth, And The Economic Well-Being Of Farm Households." *U.S. Department of Agriculture, Economic Research Service* (2002): n. pag. Web. 13 Nov. 2016.

Mishra, El-Osta, and Gillespie. "Effect of Agricultural Policy on Regional Income Inequality among Farm Households." *Journal of Policy Modeling* 31.3 (2009): 325-40. Web.

Monnat, Shannon M., Lawrence E. Raffalovich, and Hui-shien Tsao. "Trends in the Family Income Distribution by Race/Ethnicity and Income Source, 1988-2009." *Project MUSE - Trends in the Family Income Distribution by Race/Ethnicity and Income Source, 1988-2009*. Sociological Demography Press, 2012. Web. 17 Oct. 2016.

Muller, A. "Education, Income Inequality, and Mortality: A Multiple Regression Analysis," BMJ, 324, 2002.

"Nebraska Agriculture Fact Card." *Nebraska AGRICULTURE* (2013): 5-30. Print.

Norton, M. I., and D. Ariely. "Building a Better America--One Wealth Quintile at a Time." *Perspectives on Psychological Science* (2011): 9-12. Print.

"Reporting Farm Income and Expenses." *Reporting Farm Income and Expenses*. United States IRS, 1 June 2007. Web. 24 Nov. 2015.

Thompson, Eric, Bruce Johnson, and Anil Giri. "The 2010 Economic Impact of the Nebraska Agricultural Production Complex." *Department of Agricultural Economics* 192 (2012): ii-29. Print.

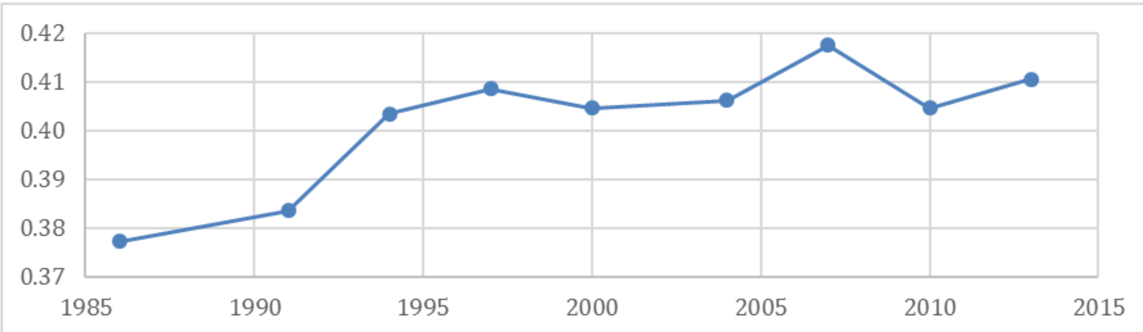
USDA. 2012 U.S. Census of Agriculture, "Highlights Family Farms." National Agricultural Statistics Services. March 2015. Web.

USDA. Economic Research Service, "Farm and Nonfarm Household Comparability," Income, Wealth, and the Economic Well-Being of Farm Households/AER-812.

Weinberg, Daniel. "U.S. Neighborhood Income Inequality in the 2005–2009 Period." *American Community Survey Reports* (2011). Print.

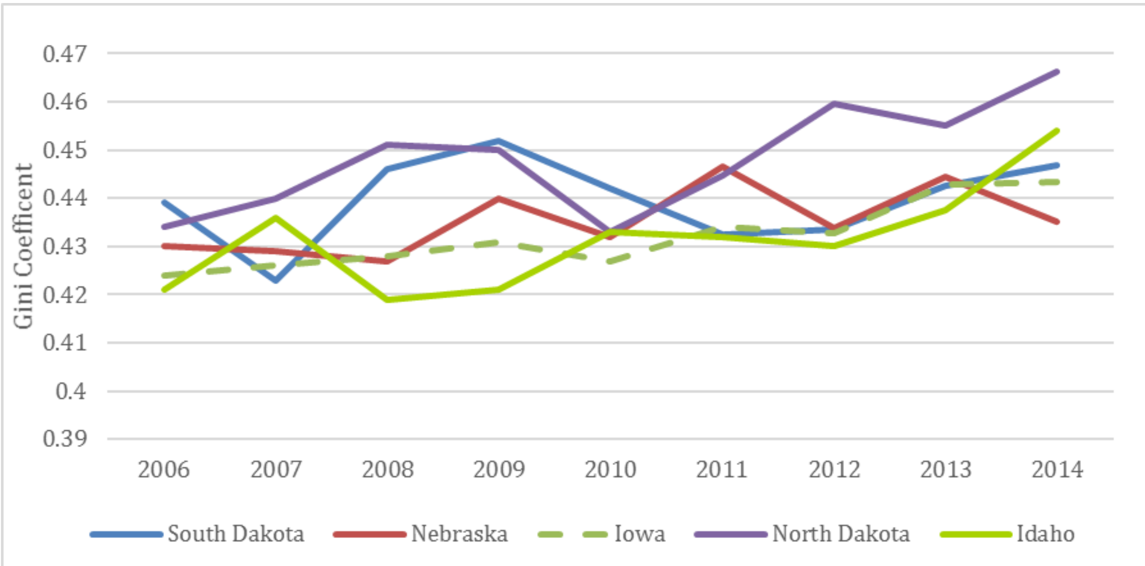
Yellen, Janet. "Speech to the Center for the Study of Democracy." 2006-2007 Economics of Governance Lecture. Irvine, California. 6 Nov. 2006. Lecture.

Figure 1: United States Gini Coefficient, 1986-2013



Source: World Bank

Figure 2: Increase in Gini Coefficient in Farm States, 2006-014



Source: U.S. Census Bureau

Table 1: Description of county data by Gini Coefficient, 2014							
Quintiles	Gini average	Farm income as share of total income	Percent white	Percent of births to unmarried mothers	Median Age	Percent with a high school degree	Population Density
1	0.388	0.168	94.9%	23.2%	41.5	33.1%	43.7
2	0.414	0.157	92.7%	29.3%	42.1	32.3%	24.6
3	0.428	0.122	93.7%	27.6%	42.1	30.6%	41.9
4	0.445	0.163	92.4%	26.5%	42.8	30.0%	39.3
5	0.482	0.173	84.7%	31.4%	41.8	31.8%	20.9

Table 2: Profile of counties by Gini score, 2014					
	Percent of counties by Gini quintile				
Gini Quintile	North Dakota	South Dakota	Nebraska	Iowa	Idaho
1	5.7%	13.6%	23.7%	23.2%	31.8%
2	11.3%	18.2%	23.7%	23.2%	15.9%
3	15.1%	15.2%	20.4%	26.3%	20.5%
4	20.8%	21.2%	20.4%	19.2%	18.2%
6	47.2%	31.8%	11.8%	8.1%	13.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%

Table 3: Correlation coefficients with Gini Coefficient, 2010-2014						
All states	All states	IA	ID	ND	NE	SD
Farm income as % PI	0.059	-0.061	-0.283	-0.024	0.141	0.047
Percent white	-0.324	-0.329	0.099	-0.442	-0.145	-0.332
Percent births to unmarried mothers	0.151	0.136	0.021	0.096	0.017	0.258
Age	-0.033	-0.118	0.118	-0.175	0.046	-0.191
Percent HS	0.005	-0.277	-0.190	-0.003	0.002	0.072
Population density	0.010	0.203	0.157	-0.031	0.073	-0.078
Number of observations	1,775	495	220	265	465	330

Table 4: Variable definition for regression variables	
Variable Name	**Definition of Variable**
Gini (the dependent variable)	2010-2014 Gini coefficients for each county in the five state area.
Farm income as a share of total income	2010-2014 Farm income as a percentage of the total income for all counties In all 5 states.
Median Age	Median age of the population for all counties
Percent High School	Percentage of the population with a high school or higher educational degree
Population Density	County population per square mile
Percent White	Percentage of white population out of total population.
Percent Birth	Percentage of births to unmarried mothers out of the total births for each year.
Iowa	A binary variable equal to 1.0 for all Iowa counties, and equal to 0 for all non-Iowa counties
Nebraska	A binary variable equal to 1.0 for all Nebraska counties, and equal to 0 for all non-Nebraska counties
South Dakota	A binary variable equal to 1.0 for all South Dakota counties, and equal to 0 for all non-South Dakota counties
North Dakota	A binary variable equal to 1.0 for all North Dakota counties, and equal to 0 for all non-North Dakota counties
INE	Nebraska's farm income as a percent of total income times the indicator variable, Nebraska.
ISD	South Dakota's farm income as a percent of total income times the indicator variable, South Dakota.
IIA	Iowa's farm income as a percent of total income times the indicator variable, Iowa
IND	North Dakota's farm income as a percent of total income times the indicator variable, North Dakota.

Table 5: Factors influencing 2010-2014 county Gini Coefficients, Equation (1) and (2)		
	Equation (1) Coefficient (Standard Error)	Equation (2) Coefficient (Standard Error)
Intercept	0.465* (0.008)	0.451* (0.008)
Farm income as % Personal income	0.00001 (0.008)	-0.0002 (0.008)
Age	0.001** (0.0002)	0.0008** (0.0002)
Percent HS	0.00007 (0.0004)	-0.0002 (0.0002)
Pop Density	0.00002** (7.62e-06)	0.00002** (9.16e-06)
Percent Birth	-0.001 (0.005)	-0.001 (0.005)
Percent White	-0.110** (0.009)	-0.083** (0.008)
YR2011	0.003 (0.002)	0.003 (0.002)
YR2012	0.006** (0.002)	0.006** (0.002)
YR2013	0.012** (0.002)	0.012** (0.002)
YR2014	0.014** (0.002)	0.014** (0.008)
Iowa		0.001* (0.003)
North Dakota		0.019** (0.003)
Nebraska		0.004 (0.024)
South Dakota		0.029** (0.003)
Number of observations	1,775	1,775
R-SQ	0.161	0.243
F value	24.43	33.15
Robust standard errors in parentheses *, & **, represent 90% and 95% level of confidence, respectively.		

Table 6: Factors influencing county Gini Coefficients, Equation (3)	
	Coefficient (Standard error)
Intercept	0.463 ** (0.009)
Farm income as % Personal income (IIA)-Iowa	0.065 ** (0.029)
Farm income as % Personal income (IID)-Idaho	-0.086** (0.023)
Farm income as % Personal income (IIND)-North Dakota	0.102** (0.028)
Farm income as % Personal income (IINE)-Nebraska	0.014** (0.004)
Farm income as % Personal income (IISD)-South Dakota	0.116** (0.006)
Age	0.0006** (0.001)
Percent HS	-0.0001 (0.0002)
Pop Density	0.00002** (9.30e-06)
Percent Birth	-0.001 (0.004)
Percent White	-0.079** (0.008)
Nebraska	-0.012** (0.004)
South Dakota	0.013** (0.004)
Iowa	-0.002 (0.009)
North Dakota	0.020** (0.004)
YR2011	0.002 (0.002)
YR2012	0.006** (0.002)
YR2013	0.012** (0.002)
YR2014	0.014** (0.002)
Number of observations	1,775
R-SQ	0.255
Robust standard errors in parentheses; *, and **, represent 90% and 95% level of confidence, respectively.	

Figure 3. Government Support Payments by State 2010-2014

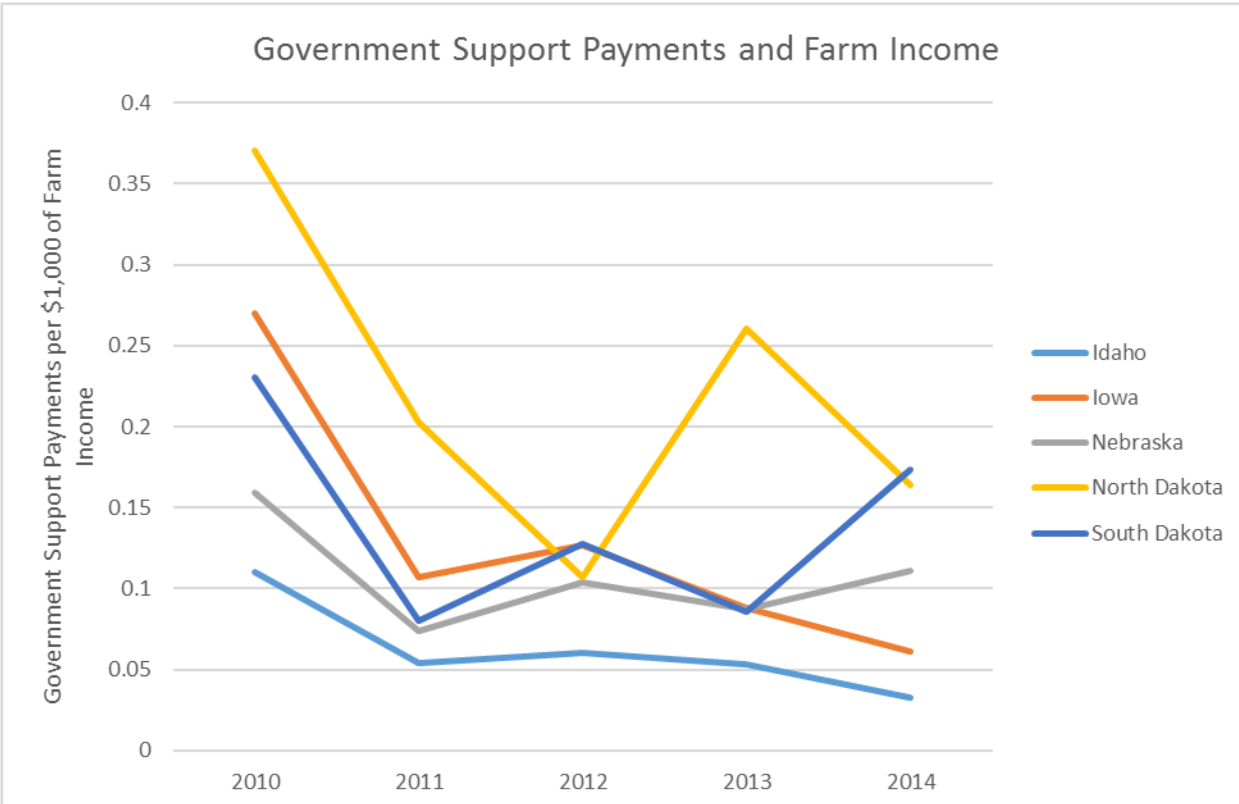


Table 7: Gini Coefficients, rankings and farm support payments as percent of farm income, 2014		
	Actual Gini (U.S. ranking)	Government support payments as % of farming income
Iowa	0.4358 (6)	6.60%
Idaho	0.4375 (7)	3.30%
Nebraska	0.4383 (9)	11.10%
South Dakota	0.4404 (10)	17.30%
North Dakota	0.4535 (21)	16.40%
Sources: Gini Coefficients, U.S. Census Bureau; Government support payments, U.S. Bureau of Labor Statistics		

Table 8: Factors influencing 2010-2014 county Gini Coefficients, Equation (1)		
	Government farm support payments as % of personal income	
	Equation (1)	Equation (2)
Intercept	0.465** (0.008)	0.451** (0.008)
Gov't payments as a % of farm income	-0.003* (0.002)	-0.003** (0.001)
Age	0.001** (0.0002)	0.0008** (0.0002)
Percent HS	0.00007 (0.0004)	-0.0002 (0.0003)
Pop Density	0.00002** (7.52e-06)	0.00002** (9.16e-06)
Percent Birth	-0.0003 (0.005)	-0.0007 (0.005)
Percent White	-0.11** (0.009)	-0.083** (0.008)
2011	0.002 (0.002)	0.002 (0.002)
2012	0.005** (0.002)	0.005** (0.002)
2013	0.011** (0.002)	0.011** (0.002)
2014	0.013** (0.002)	0.013** (0.002)
Nebraska		0.001 (0.003)
South Dakota		0.019** (0.003)
Iowa		0.004* (0.025)
North Dakota		0.029** (0.003)
Number of observations	1,775	1,775
R-SQ	0.1617	0.2429
F value	24.44	33.73
Robust standard errors in parentheses; *, and **, represent 90% and 95% level of confidence, respectively. 2010 is the omitted comparison group.		