A cross-country analysis of income inequality

Evidence that strong and sustained economic growth can be a leveler of income.

In an attempt to associate income inequality with certain forces or conditions in the economy we draw a sample of 53 countries to isolate which, if any, economic or demographic variables explain the cross-country differences in income inequality. As a result we identify influences statistically associated with the cross-country differences in the Gini Coefficient.

Developed by Corrado Gini, an Italian professor (circa 1920), the Gini Coefficient is a measure of income inequality. A Gini coefficient of zero is associated with an equal income distribution, i.e., everyone earns the same income. A Gini of zero is not necessarily ideal as everyone could be equally poor/impoverished/destitute. A Gini of one could indicate that a single individual earns all the income and everyone else earns nothing. This outcome is not necessarily bad if that individual provides the support for everyone else (as in some households). Therefore, the Gini Coefficient does not measure well-being or wealth. As a consequence no one Gini value can be proven superior to any other Gini value.

However, for economies as a whole the Gini can be used as a comparative measure of income distribution amongst the various countries. Identifying the conditions that lead to cross-country income distribution can, perhaps, shed light on those forces within an economy that determine or at least help explain intra-country income distribution. Straightforward multiple linear regression identifies a set of correlates that significantly influence the inter-country Gini. For the most part the variables identified are intuitive. That is, the influencing variables can be easily reconciled with simple notions of human behavior.

The most significant variable ($\alpha < .0001$) influencing the Gini coefficient is the *median age* of the population (2014). All variables are estimates gleaned from tables published by the US CIA. (Central Intelligence Agency, 2016, *The World Factbook*, https://www.cia.gov/library/publications/resources/the-world-factbook.) The most prominent finding is a highly significant and negative coefficient for the median age variable. That is, older populations are associated with lower Gini coefficients. As individuals age there is less disparity in their incomes. Retirement from productive endeavors is an obvious leveler of income differences. In addition, the incentive to pursue ever-higher incomes diminishes as workers approach retirement producing the well-established age-earnings curve.

The percentage of GDP devoted to *investment* in capital goods is the second most significant variable ($\alpha < .001$). The sign of the investment coefficient is positive indicating that those economies spending the greater percentage of GDP on investment generally have higher Gini coefficients. This result suggests that countries devoting the most effort to capital investment experience greater *current* income inequality as investment, if successful, produces greater *future* incomes. The Gini, of course, measures contemporary income distribution. In this manner, a higher Gini (greater current inequality) maybe the price for promised higher incomes and greater future economic welfare.

The coefficient for *agriculture* (percentage of population engaged in agriculture) is negative and is third in significance ($\alpha < .001$). That is, as more of the population is employed in agriculture inequality diminishes. The negative sign is not unexpected as it could be theorized that the income distribution within the agriculture sector experiences less dispersion than other sectors. A totally agrarian society would produce less income dispersion among its participants than a widely diversified economy.

Economic growth (percentage change in GDP) exerts a negative influence on Gini meaning that inequality is reduced by economic growth. More rapid economic growth raises low incomes at a faster *rate* than high incomes ($\alpha < .01$).

Higher rates of *unemployment* have a positive influence ($\alpha < .05$) on Gini meaning that greater unemployment rates correlate with higher Gini Coefficients, that is, greater inequality. With more unemployment comes greater income inequality as more of the population earns little or no income.

The last significant identifiable variable is the percentage of GDP paid in *taxes.* The sign of the tax variable is negative confirming the notion that higher taxes tend to lessen income inequality ($\alpha < .01$). That is, tax policies generally impose a greater burden on those with higher incomes.

Taken collectively the above variables explain 77 percent of the variation in the inter-country Gini coefficient and have a level of significance well beyond any conventional level. ($\alpha <$ .ooooo1). However, 23 percent of the variation in Gini remains unexplained. The regression's constant term is the most significant. While the 'missing' variables are unknown they collectively 'explain' almost one-fourth of the variation in inter-country Gini coefficients. We find that the variables measuring inflation, per capita GDP, and expenditures on education do not significantly affect the Gini coefficient. The otherwise unaccounted for variables remain undetermined.

An obvious interrelationship exists among the variables of economic growth, unemployment and tax policy. Possible policy implications include actions that stimulate economic growth thereby lowering unemployment, and increasing labor force participation. These responses reduce inequality (lower the Gini) while at the same time produce positive increases in tax revenue (per dollar of GDP) thereby further lessening income inequality. The rub is finding an optimal economic policy that results in sustained and significant economic growth. *In sum, this study reinforces the long suspected notion that strong and sustained economic growth can be a powerful leveler of income inequality.*

Putting the Gini back into the bottle: A cross-country analysis* of income inequality

Evidence of causes and cures for income inequality

Coincidence or not a growing angst over income inequality surfaced following the financial collapse of 2009. Millions of workers disappeared from the work force and have not yet returned magnifying the gap between households at one end of the income spectrum from the other. A growing concern over the existing income distribution emerged as a public policy issue but no one has yet defined what is the optimal income distribution. A definition will not be presented herein for as in beauty and fairness the optimal income distribution lies in the eye of the beholder. Having said that, most would agree that lessening the gap is a worthy goal.

At least some of the income disparity can be attributed to 'natural' causes and as such represents a policy challenge. For instance, the age of the population demonstrates a profound influence on what social sciences call the Gini Coefficient. The Gini is a measure of income inequality applicable to both small and large populations. A Gini of zero indicates that everyone in the defined group shares income equally. This outcome is not necessarily good as everyone could be equally poor/destitute. A Gini of one means that one worker earns all the income and everyone else zero. This outcome is not necessarily bad as many households depend upon the earnings of a single individual.

Growing out of a graduate research assignment a simple statistical analysis involving 53 countries finds that the Gini varies inversely with the median age of the population. That is, the older the population the lower the Gini or less inequality. Hopefully, population control is beyond the reach of public policy.

This same statistical analysis finds that the percent of the population employed in the agriculture sector is negatively related to the Gini. That is, the greater percent of the population engaged in agriculture the lower the Gini. This result can also be attributed to 'natural' causes often shaped by centuries of evolving social and economic development and to the geographical climate. Public policy may exert some influence on the agriculture variable but only over a very long term. For the short term this variable is taken as a given.

A similar conclusion applies to GDP growth. Greater GDP growth generally results in less income inequality (lower Gini). Astute public policy can support GDP growth but vigorous debate exists as to what is astute and what isn't. Unfortunately, much of the debate is ideological and thereby itself not astute.

The public policy that influences Gini the most is tax policy. The higher the overall tax rate (taxes revenues/GDP) the lower the Gini. Most governmental tax policy (but not all) taxes higher incomes at a greater rate than lower incomes. But taxation is a double-edge sword as taxes may act as a deterrent to productive (income and job creation) behavior. Fortunately, it's possible to design tax policy that encourages economic growth in the short term while raising government revenue in the long term. (See investment below.)

Public policy that reduces unemployment also has the property of reducing Gini. That is, less unemployment lowers income inequality. This finding is intuitive as is the findings for median age and income growth. It's comforting to learn that statistical analysis confirms what common sense dictates.

Interestingly, investment (annual increases in productive assets) influences income inequality negatively. This seemingly counter intuitive result arises because investment expenditures produce GDP growth at a lag while detracting from current consumption.

In sum, the measures identified above explain more than 75 percent of the variation in the Gini coefficient. However, 25 percent remains to be explained by missing (unidentified) variables. Equally interesting is the discovery of which measures have no measurable influence, at least as evinced in the present study, on income inequality. That list includes inflation, years of schooling, GDP per capita, and government deficits (as a percent of GDP).

Putting these results into perspective suggests that some income inequality emanates from environmental forces and normal human behavior. However, public policy may exert a positive influence on reducing income inequality through economic policy that promotes economic growth, lower unemployment, greater labor force participation and appropriate tax policy. In sum, the overarching conclusion of this analysis is that sustained and significant economic growth acts as a leveler of income inequality. Public policy would best be structured toward that end.

* Supporting data and statistical analysis are available from the author by request.

Hi Bryan,

Let me take your queries one at a time:

- I assigned a graduate student the task of determining how age (median age in any given country) influenced income inequality (as measured by the Gini Coefficient). The student sampled just over 30 countries. I decided to expand the sample to include 53 countries and added nine other socio-economic variables to the mix.

- I included as many countries as I reliably dared (I exempted countries like Cuba, Venezuela, Viet Nam, Mali, etc. you get the idea.) Attached to this message is a table of the countries and variables included in the original study as well as a statistical analysis of all sample countries and all sample variables. I also excluded variables that I felt had very little explanatory power or who's reliability was questionable.

- I dropped from the final statistical analysis variables that did not exhibit any standard level of significance, e.g., $\alpha = .05, .02,$ or $.01$. That is, variables that chance alone could have caused their inclusion. Thus, the surviving variables stood the statistical test for significance.

- You are correct about the classification of variables into 'natural' or policy driven.

- Here is a list of the included variables ranked by their significance:

1. Intercept (constant) (t=10.727)
2. Median age (t=-6.346)
3. Investment (t=4.013)
4. Agriculture (t=3.714)
5. GDPGRW (t=-2.634)
6. Tax (t=-2.121)
7. Unemp (t=1.624)

- The 75% (74.3%) figure represents the variables (1-7 above) the intercept included. Thus, 25% (25.7%) of the variation in Gini remains unexplained (explained by other unknown or undetermined variables).

- If the excluded variables were included the percent explained rises to 78.6%

- The last issue you raise as to how much of the variation in the Gini is due to 'natural' forces and how much to policy actions. The percent attributed to the 'natural' variables alone is 63.5%. Performing the same operation for the policy variables alone yields 36.1%. These estimates are rather tenuous because of the interaction of the variables with each other when combined and the fact there are two intercept terms.