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How Does Income Inequality Impact Economic Growth in the United States?

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ABSTRACT

This paper aims to examine the effect of income inequality on economic growth in the United States at the county level, using linear regression models to analyze the data from 2010 and 2019. Since income inequality has significantly increased in recent years, understanding its impact on economic growth, specifically through median household income, has become essential for policymakers and economists. Through statistical analysis, using linear regression of median income on the Gini index with an instrumental variable of economic connectedness, a significant causation between income inequality and economic growth was found, suggesting that higher levels of inequality can impede overall economic progress. According to the results, a 0.01 rise in the Gini coefficient results in a 12,590 dollar drop in median income for 2010 and in a 48,858 dollar drop in median income for 2019. However, only the results for 2010 are statistically significant. This might suggest that the impact of income inequality on median income is decreasing.

1. Introduction

Income inequality has become a central concern in the economic world, particularly in the United States, where disparities in wealth distribution have increased significantly over recent decades. For example, the top 1% of households held about 32% of the country's wealth in 2020, up from around 22% in 1989. Research indicates that income inequality can have immense impacts on social stability, health outcomes, and educational attainment. This poses an investigation on how income inequality impacts economic growth. As the middle class continues to shrink and wealth becomes increasingly concentrated among the affluent, understanding the implications of these trends on economic growth is crucial. The relationship between income inequality and economic growth is not only relevant for economists but also for policymakers who aim to create more inclusive and sustainable economic strategies. Given the rising urgency of these issues, quantifying the relationship of how income inequality affects economic growth can provide valuable insights for addressing structural issues in place and formulating effective solutions to these issues. As such, the research question being asked is "How does income inequality impact economic growth in the United States?"

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This study seeks to measure the empirical effect of income inequality on economic growth in the United States. This paper hypothesizes that higher levels of income inequality are negatively correlated with economic growth rates. Greater income disparity can limit access to essential resources, education, and opportunities for lower-income individuals, thereby suppressing factors like innovation and overall consumer spending, which are vital drivers of economic growth.

The analysis of this relationship will occur through creating and interpreting linear regression models, specifically with an instrumental variable of economic connectedness, due to the simultaneity between income inequality and median income. By examining historical data and trends, the research aims to provide empirical evidence that can help with discussions of new policies and improve understanding of how economic factors affect social equity.

This topic has already undergone various studies. Galor and Zeira (1993) first analyzed how income distribution influences various macroeconomic variables. They found that income inequality can significantly affect both aggregate output and investment levels, with different implications for different countries. Alesina and Rodrik (1994) expand on this topic, examining the political aspects of income distribution and its effects on economic growth through a growth framework, finding that increased inequality can lead to political instability, which ultimately hinders economic growth. Banerjee and Duflo (2003) further contribute, by using empirical data to analyze the relationship between inequality and growth. Their study shows a more complex perspective, indicating that the impact of inequality on growth can vary depending on the level of development and specific economic contexts. Building on these studies, Ostry, Berg, and Tsangarides (2014) investigate the broader implications of redistribution for growth, suggesting that redistributive policies can enhance growth by fostering a more equitable income distribution. Next, Babu, Bhaskaran, and Venkatesh (2016) focus on emerging economies to analyze whether inequality delays long-term growth. Their findings provide empirical evidence that high levels of inequality can be detrimental to sustained economic growth. Finally, to examine this topic from a post-2019 lens, to consider effects of the COVID-19 pandemic, Pizzuto, Loungani, Ostry, and Furceri highlighted how the pandemic worsened the income inequality within the nation and intensified its impact on economic growth and long-term recovery.

While these studies investigate important aspects of the relationship between income inequality and economic growth, this research is unique in the way that it investigates the impact of income inequality on economic growth, instead of the other way around. There are far more studies and more information available about this relationship, and not as much on the relationship discussed in this paper. Additionally, this paper uses recent data from 2019 and studies this relationship at the US county level. The rest of the paper is as follows: the next section discusses the methodology, it then presents the results, then goes into a discussion of these results, and the last section concludes the paper.

2. Methodology

This study employs a quantitative approach to investigate the relationship between income inequality, as measured by the Gini coefficient, and economic growth, measured by median household income in the United States. Publicly available data was sourced from the American Community Survey (ACS) conducted by the U.S. Census Bureau. The data sets selected include information from two key years: 2010 and 2019, allowing for a comparative analysis of trends over the decade. It is also at the county level, presenting each variable's data for each county in the US.

The explanatory variable is the Gini coefficient, which is a measure of income inequality ranging from 0 (perfect equality) to 1 (perfect inequality). The explained variable is the county's median income. In addition to the Gini coefficient, the analysis incorporates several control variables: age ratio (the proportion of working-age individuals to total population), racial composition ratios (proportions of different racial groups within the population), and the male-to-female ratio. These control variables were chosen to isolate the effect of income inequality by accounting for other demographic and social factors that could influence economic outcomes.

The age ratio is included because areas with a higher proportion of working-age individuals are generally expected to have higher median incomes due to greater labor force participation and productivity. The male-to-female ratio is considered because gender imbalances can affect household structure, labor market dynamics, and, consequently, income levels. It was decided to use the percentage of Black individuals as the racial composition variable for this paper, as they are often the minority group most affected by structural economic inequality in the United States. By including this percentage as a control, the bias these demographic distributions might introduce if left unaccounted for can now be regulated, as racial disparities often intersect with income inequality and may distort the relationship between inequality and economic growth. These factors were included to account for their potential influence on median household income, thereby enhancing the robustness and validity of the model's findings.

The linear regression model can be expressed as follows:

$$Median\_Income = \beta_0 + \beta_1\, Gini\_Coefficient + \beta_2 Age\_Ratio + \beta_3 Racial\_Composition + \beta_4 Male\_to\_Female\_Ratio + \varepsilon$$

Where β_0 is the intercept, β_1 through β_4 are the coefficients for the independent variables, and ε represents the error term. The results from the regression analysis will provide insights into how variations in the Gini coefficient correlate with changes in median household income, while controlling for demographic factors.

However, this was still biased. Since economic growth and income inequality supposedly affect each other simultaneously, an instrumental variable was needed in order to ensure that we could isolate the causal effect of income inequality on median income and make sure no other factors were affecting the regression. To do this, social capital data, obtained from Opportunity Insights[1] was used. Opportunity Insights is an organization that aims to develop solutions to economic barriers that US citizens might face to help them rise out of poverty and have a better life. They also provide economic data available for public use. This paper uses the variable of economic connectedness. Economic connectedness is the degree of interaction between people of different income levels, or the percentage of high-income friends among low-income people. This variable is shown to be correlated with income inequality but supposedly does not affect economic growth directly, only through its effect on income inequality. So, when performing the regression, this is able to identify the effect of changes in income inequality on median income. This eliminates the simultaneity bias in the estimation.

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[1] *Data | Opportunity Insights*. (2014). Opportunityinsights.org. https://opportunityinsights.org/data/

3. Results

The regression analysis showed important findings about the relationship between income inequality and median household income in the United States for the years 2010 and 2019, as summarized in the regression tables below. Based on these results, the hypothesis of there being a negative relationship between the Gini coefficient and median income is accepted for the year 2010 but not supported for 2019.

To start, the 2010 analysis displayed a statistically significant negative relationship between the Gini coefficient and median income, with a coefficient of -1.259 million and a p value of 0.004. This means that if the Gini coefficient increases by 1, the impact on median income is that it decreases by 1,259,000 dollars. The share of the Black population had a coefficient of 61,520, so a one percentage point change in the share of Blacks in a county is associated with an increase of $61,520 dollars in median income. However, this has a p value of 0.087, approaching significance, but not quite reaching it yet, which suggests that higher proportions of Black residents may correlate with lower median income levels. This means that determining the exact relationship would require further investigation. The age ratio in this year had a coefficient of -417.54 and a p value of 0.231, indicating no significant effect on median income. Notably, the male-to-female ratio showed a statistically significant negative coefficient of -868.14, having a p value of 0.024. So, an increase in the sex ratio, or if a county has more men than women the median income of that county could decrease proportionally to $868,14. This suggests that disparities in gender ratios are associated with lower median income levels. This finding emphasizes the potential socioeconomic implications of gender imbalances in the workforce. The overall R^2 for the 2010 model was -5.089, with an F-statistic of 5.910 and a p value of 0.000158, indicating that this model was statistically significant.

For 2019, the regression results indicated a negative coefficient for the Gini coefficient of -4.858 million. This shows an inverse relationship between the Gini coefficient and median income. This would mean an increase of the Gini coefficient by 1, would cause a decrease of $4,858,000 in median income. However, in contrast to 2010, this result was not statistically significant, with a p value of only 0.458. Among the control variables, the share of the Black population had a coefficient of 77,709, with a significant p value of 0.855, indicating no significant effect on median income. The age ratio approached significance with a coefficient of -5,358.66, having a p value of 0.057, suggesting that an increase in the age ratio may be associated with a decrease in median income. So, an increase of the age ratio may cause a decrease in median income would cause a decrease proportional to $5,358.66 in median income for a county. The male-to-female ratio displayed a coefficient of -6,321.08 and a p value of 0.201, indicating a negative association with median income, but this result did not reach statistical significance. The overall R^2 value for the model was -0.300, with an F-statistic of 2.582 and a p value of 0.0383, suggesting that the model is statistically significant.

When comparing the regression results for 2010 and 2019, there are several notable differences regarding the impact of income inequality and demographic factors on median household income. In 2010, a significant negative relationship was found between the Gini coefficient and median income, with a coefficient of -1.259 million (p = 0.004), indicating that higher income inequality was directly associated with lower median income. Conversely, in 2019, the Gini coefficient had a negative coefficient of -4.858 million (p = 0.458), but this relationship was not statistically significant, suggesting that the impact of income inequality on median income had weakened over the decade. The demographic variables also showed contrasting trends. While the share of the Black population approached significance in 2010 with a coefficient of 61,520 (p = 0.087), indicating a potential correlation with lower median income, it was not significant in 2019 (coefficient of 77,709, p = 0.855). Additionally, the male-to-female ratio displayed a significant negative impact in 2010 (coefficient of -868.14, p = 0.024), whereas its effect in 2019 was negative but not statistically significant (coefficient of -6,321.08, p = 0.201). Overall, these findings suggest a changing dynamic in the relationship between income inequality and median income over the ten-year period, with demographic factors also demonstrating more diverse effects.

Table 1: Regression Results

Dependent Variable: Median Income	*(1)*	*(2)*	*(3)*	*(4)*
	OLS	OLS	IV	IV
Gini	-4.192E+04	1.86E+06***	-1.259E+06***	-4.858E+06
	(0.114)	(0.009)	(0.004)	(0.458)
share_Black	-2.99E+04***	-3.334E+05***	6.152E+04*	7.709E+04
	(0.000)	(0.007)	(0.087)	(0.855)
Age	-896.3300***	-6988.5895***	-417.5358	-5358.6581*
	(0.000)	(0.000)	(0.231)	(0.057)
Gender_Males_to_Females	-72.4477	-1,715.3884	-868.1408**	-6,321.0799
	(0.350)	(0.338)	(0.024)	(0.201)
Year	2010	2019	2010	2019
Observations	216	216	216	216

An important factor in these regressions was the instrumental variable, economic connectedness. While economic connectedness promotes a more equitable income distribution, affecting the Gini coefficient, it does not directly elevate median income levels, as broader economic conditions tend to affect median income. Economic connectedness only affects median income levels through affecting the Gini coefficient. To prove this relationship, first stage regressions were done to determine the extent to which economic connectedness affects income inequality through the Gini coefficient. These regressions indicate notable trends between the two variables. In 2010, the coefficient for economic connectedness was -0.0420, significantly associated with a lower Gini coefficient because of the p-value of 0.003, suggesting reduced inequality. So if economic connectedness increased by 1, the Gini coefficient would decrease by 0.0420. By 2019, this coefficient decreased to -0.0320, indicating a weaker but still significant negative relationship with a p-value of 0.031. So in 2019, if the economic connectedness in a county increased by 1, their Gini coefficient would decrease by 0.0320. In both years, a statistically significant trend was seen: higher economic connectedness caused lower income inequality.

Table 2: First Stage Regression

Dependent Variable: Gini	*(1)*	*(2)*
Economic Connectedness	-0.0420***	-0.0320**
	(0.003)	(0.031)
share_Black	0.0544***	0.0457***
	(0.000)	(0.001)
Age	0.0002	0.0002
	(0.492)	(0.415)
Gender_Males_to_Females	-0.0006***	-0.0006***
	(0.002)	(0.000)
Year	2010	2019
Observations	216	216

4. Discussion

The findings from this study illuminate significant trends and changes in those trends within the relationship between income inequality and median household income, in the United States over the decade from 2010 to 2019. The strong negative association found in 2010 aligns with previous research suggesting that higher income inequality, as measured by the Gini coefficient, adversely affects overall economic well-being and can exacerbate disparities in income distribution (Galor & Zeira, 1993; Alesina & Rodrik, 1994). However, the lack of significant correlation in 2019 raises questions about how the dynamics for income inequality and its implications for economic growth have evolved. One possible reason could be that median income levels in 2019 may have been influenced by other factors, such as economic recovery post-recession, technological advancements, or changes in labor market policies, which might have mitigated the impact of inequality during that period. More controls may have to be added due to the change in time period. Additionally, since 2019 was on the border of the pandemic, that might affect certain variables.

Moreover, the findings on some of the demographic factors provide further insight into how complex income distribution truly is. The marginal significance of the age ratio in 2019 suggests a potential relationship that warrants deeper investigation, as an aging population may affect labor force participation and productivity, therefore, affecting median income. The fact that the share of the Black population and the male-to-female ratio showed varied significance across the two years reflects the more complex and layered realities of social dynamics and wealth classes. These variations highlight that while some demographic factors may correlate with income levels, their effects can fluctuate based on broader economic contexts and societal changes.

It is also essential to acknowledge the limitations of this study. The use of the Gini coefficient as a sole measure of income inequality may oversimplify the complexities of economic disparities, as it does not capture the full spectrum of wealth distributions. Additionally, the regression analysis relies on historical data from the American Community Survey, which may not fully account for changes in economic conditions that occurred after 2019, especially given the pandemic that occurred after. This study may not be applicable now, in 2024. Therefore, further research incorporating more qualitative assessments could provide more insights into the relationships between these variables.

Policymakers should consider inequality not just as a social justice issue, but as a macroeconomic concern. Strategies such as investing in early childhood education, increasing access to affordable healthcare, and promoting inclusive labor markets may help mitigate the long-term effect of inequality on economic growth. Furthermore, policies should work to foster economic connectedness, by reducing social segregation and promoting cross-class interactions, which could ultimately improve equity and productivity.

Ultimately, while the research supports the hypothesis that income inequality negatively impacts median household income, the findings also suggest a need for more understanding of this relationship, due to the many other layers that could be considered. As economic conditions evolve, so too must our methods for analyzing income distribution and its effects on society. These results highlight the importance of ongoing investigation into how demographic factors intersect with economic indicators, particularly in a time period that is known for its rapid social and technological change.

5. Conclusion

In conclusion, this study examined the relationship between income inequality, as measured by the Gini coefficient, and economic growth, measured by median household income in the United States, focusing specifically on data from 2010 and 2019. The findings supported the hypothesis that income inequality negatively impacts median income in 2010, highlighting a significant correlation. However, this relationship was not statistically significant in 2019, suggesting a potential shift in the dynamics affecting income levels. This indicates that while income inequality may have profound effects during certain economic conditions, other factors may play a more critical role over time, emphasizing the need for a more nuanced understanding of these relationships.

Given these insights, future research should explore the means behind the changing impact of income inequality on economic outcomes, possibly by incorporating more qualitative data and more control variables. Additionally, policymakers should consider strategies that address income inequality while also promoting economic growth, ensuring that their methods are considerate of demographic changes and evolving economic conditions. By adopting a diverse approach to studying income distribution, we can better understand its complexities and develop more effective solutions to foster equitable economic development.

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