An Empirical Analysis of the Status of Income Inequality New England in 2022

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Abstract:

This paper investigates the status of income inequality within the New England states in 2022. The empirical analysis conducted within this paper uses a similar model within Fadi Fawaz et al. for high income countries to analyze and predict the Gini coefficient within the six New England States. More specifically, the model that is tested analyzes monthly unemployment rate, the labor force participation rate, welfare spending, and the top 1% wealth distribution. The results show that Rhode Island and Maine Gini indexes could only be described by the top 1% wealth distribution and welfare spending, respectively. We also find that a large welfare spending budget yields greater income inequality in states that have a larger spending budget, more specifically Massachusetts being a prime example. Outside of New Hampshire, an increasing labor force participants effectively decreases income inequality. Finally, we found that any directional change in the unemployment rate does not have a noticeable impact on income inequality. With limitations, we found that there is inclusive evidence that certain macroeconomic indicators can affect the Gini index within the six New England states, more specifically income inequality.

JEL Classification: O15, D31, I24, I28, I12, I14
Keywords: Income, Income Inequality, Gini, Health, Education, Government Policy

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1.0 INTRODUCTION

Today, the interconnectedness of the world has allowed everyone to be more aware of the crucial problems like income inequality. Income inequality is one of the more prominent problems in modern society, especially in the free market economy of the United States. One of the many models in economics that describes income inequality, more specifically economic inequality, is the Lorenz curve. The Lorenz Curve was developed by economist Max Lorenz with the intention to describe inequality in respect to wealth distribution. Another significant and popular way of measuring income inequality with the Gini coefficient. The relationship between the two variables is relatively straightforward: the Lorenz curve shows the “gap” that represents how well wealth is distributed while the Gini coefficient represents the severity of income inequality in an index. This study will analyze what macroeconomic indicators, among others, affect the Gini coefficient overall. Throughout this paper, we will analyze certain trends with our indicators that we will be analyzing between 2010 and 2022. In that 12 year span, many historical events have occurred that have likely been a huge transition period for the economy such as the aftermath of the 2008 financial crisis and the COVID-19 pandemic. Additionally, this paper will be looking back at previous literature and analyzing what past research has found. Many recent papers have argued that researchers before them often “overlooked” certain indicators to which they believe would have been a massive determinant towards describing what affects the Gini coefficient, or income inequality in general. In hindsight, there are many pathways that researchers could have gone down and found credible results. Although sometimes this argument can be rather invalid considering modern events going on around the world (i.e. a pandemic) having a collateral effect on certain things in the economy. Despite that, this paper will continue research in the field of income inequality. By collecting data from the U.S. Census Bureau and the St. Louis Fred, we will be determining what macroeconomic indicators (more specifically, the labor force participation rate, per capita income, and the unemployment rate) among others such as the (TBD). Based on the analysis, we will conclude what indicators have had the most impact over the last decade.

2.0 TREND (OF THE GIVEN TOPIC)

Figure 1 shows how the Gini coefficient has changed over the last 12 years within Massachusetts, Rhode Island, New Hampshire, Vermont, Connecticut, and Maine. In 2012, the variation of the Gini coefficient between the six states in the region was .034 (between .465 and .431). By 2022, the range grew from .034 to .83 (between .519 and .431). For a majority of the 12 years that we collected our sample from, New Hampshire almost always had the lowest Gini coefficient, meaning the state was the most equal income wise. Connecticut was constantly the state with the highest Gini coefficient until 2021 when Massachusetts saw a large increase in their respective Gini from 2021 to 2022.

Figure 1:

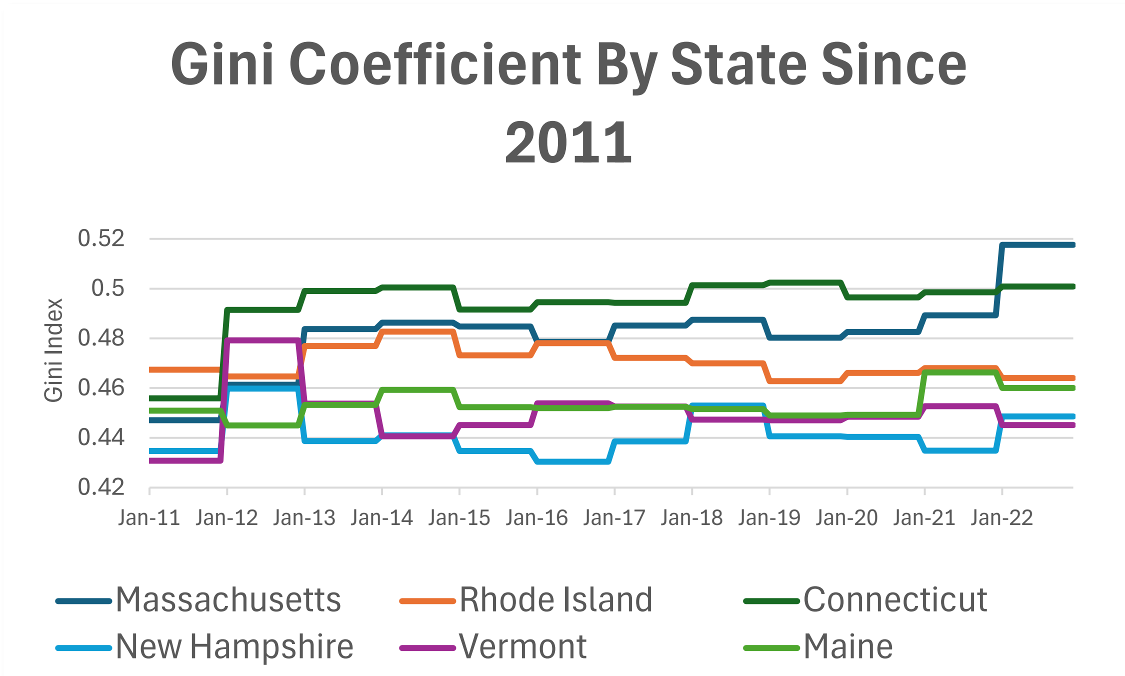
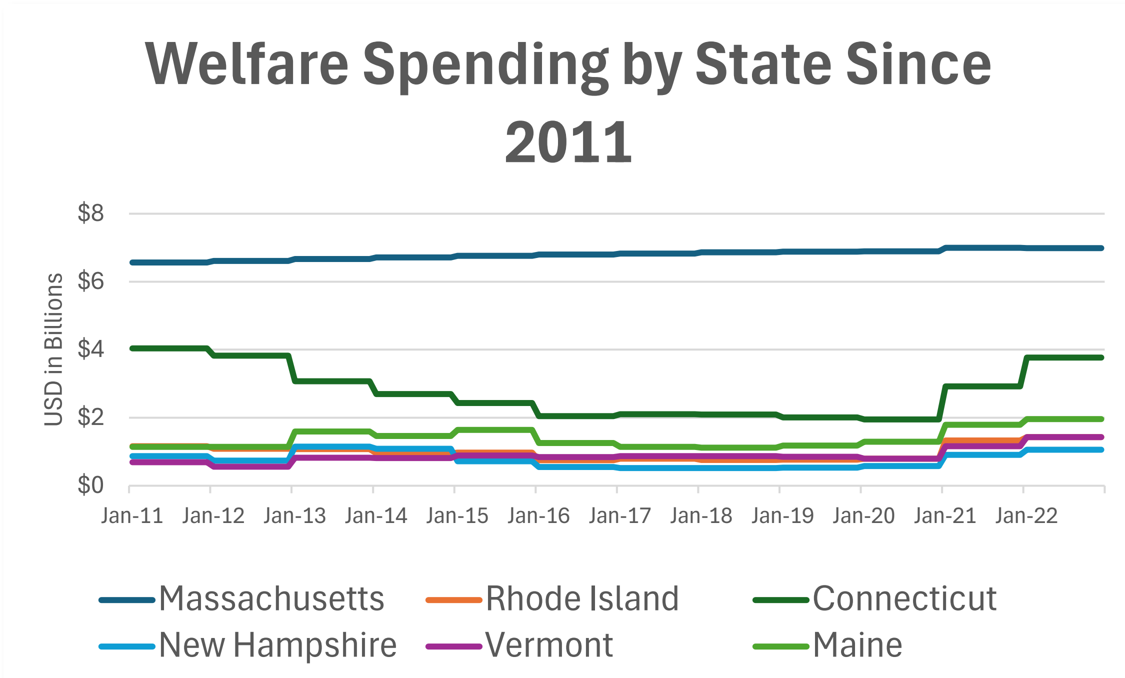


Figure 2 shows welfare spending by state in the same period. Massachusetts welfare spending was the highest average spending per year with roughly $7 billion. Between 2016 and 2020, each state was relatively consistent with their spending. Connecticut had the largest dip in welfare spending between 2012 and 2016, but then proceeded to see a $2 billion increase in spending between 2021 to present. In 2016, New Hampshire, Rhode Island, and Vermont were all spending less than $1 billion in welfare spending. Finally, in terms to the labor force participation rate, the largest average labor force participation rate was new Hampshire with 68%. The variation for averages in the LFPR was roughly 6%, showing some consistency within all states.

Figure 2:



3.0 LITERATURE REVIEW

Analyzing income inequality, no matter the size of the region, country, or area, has been practiced using the Gini Coefficient. The United States has been tracking the Gini coefficient since 1963, according to the St. Louis Fred. Over the last 60 years, the U.S. has seen periods of an increasing Gini coefficient. The index ranges from zero (0) to one (1) where 0 is perfect equality and 100 is perfect inequality. According to FRED, the data collected to generate an index number is "household survey" data obtained from various areas in the government. With that, previous papers have used this coefficient to highlight social inequality, more specifically, income inequality. The motivation behind previous papers have noted that past research papers "have failed" to look at the impact of income inequality across citizens, such as Newman et al. (2015). Newman et al. (2015) motivation came from the lack of research from previous papers when it comes to focusing on a smaller segment of people (i.e., residential areas) and wanted to see if economies that are more government controlled (or economies with more government intervention) have a lower

Gini than more free-market economies. The results from the paper showed that a government-controlled economy shows no differences in income inequality in comparison to the standard free-market economy. Like Newman et al. (2015), Wilkinson and Pickett (2009) were not satisfied with previous research, more specifically the research in income inequality and health. In their research, Wilkinson and Pickett (2009) wanted to see if there was a relationship between income status and social health (i.e., educational attainment, educational enrollment, mental illness, violence, obesity, drug abuse, etc.). The findings in this paper showed that the more someone were to look at lower income classes, the worse the "social health" would be, meaning that one of the examples of poor "social health" would be present. With that, there is a direct relationship between income and social health. Curran and Mahutga (2018) also look at the relationship between income and overall human health. Like Wilkinson and Pickett (2009), Curran and Mahutga (2018) also found that there is a direct relationship between income and health. In fact, Curran and Mahutga (2018) also found that health declines exponentially the further down one would go in the income bracket.

Schneiders and Hastings (2017) wanted to continue research by looking at household spending on services. Both of their findings showed that there was a direct relationship between household spending on services and income. Duncan and Murnane's (2016) motivation comes from previous research looking at education and income inequality. This time, Duncan and Murnane (2016) analyzes the effect of certain government policies on educational attainment levels in respect to income inequality with before-and-after empirical analysis. Results showed that there was in fact very little success, if any, when it came to current government policies in place to increase all levels of education enrollment. Finally, Fawaz et al. (2012) analyzes income inequality with the Gini coefficient in high-income developing countries (referred to as HDICs) and low-income developing countries (referred to as LDICs). He and others found that human capital and economic uncertainty were two of the largest impacts on growing income inequality. The first model shown in Fawaz et al. (2012) is the inspiration behind this empirical analysis. In the model, use the Gini coefficient (continuous variable) as their dependent variable. The independent variables in Fawaz et al. (2012) that will be used in this paper are per capita income (by country), the average unemployment rate (by country), and the secondary educational attainment. In their paper, they added an additional independent variable that is per capita income squared, likely due to concern about heteroscedasticity. The variable that represents secondary educational attainment in Fawaz et al. (2012) is analyzed with a two-year lag period to hopefully make up for lack misinformation. In this empirical analysis, we will be using per capita income, unemployment, and secondary educational attainment, represented in a similar fashion like Fawaz et al. (2012). The contribution towards this area of research will be analyzing tertiary education attainment, represented in the same manner as secondary education attainment. In a scenario where the model is malfunctioned, there will likely be the addition of the effective federal funds rate as an independent variable (either as an addition or replacement towards tertiary education attainment. With the given information, this paper will continue the research from Fawaz et al (2012) and others. Additionally, the final contribution to this area of research will be adding multiple health indicators, including the number of births of women between 15 and 50 by marital status and age. More specifically, this paper will analyze trends in this field and use filtered data that will bring us to believe that it will likely influence greater income inequality. Also, our model will include disability status by age and sex year over year. Finally, this paper will also contribute to this area of research by including current data with respect to the Lorenz Curve. The Lorenz Curve is a widely known graph that represents the distribution of wealth within a population and will be used to analyze the inequality gap and actual income distribution over the years by state.

4.0 DATA AND EMPIRICAL METHODOLOGY

4.1 Data

The data for this research paper will be collected from numerous sources. First, much of the data that represents economics indicators will be from the St. Louis Fred, the U.S. Census Bureau, and the World Bank. Additionally, we will be collecting data from an independent website for tracking government spending in order to retrieve welfare spending by state, one of the variables that will be present in our logistic regression model. After the data is collected from these sources, each variable will be translated into its natural log form in order to run a logistic regression. A logistic regression will be used to identify if any of the indicators used have a growth of decaying effect on the respective Gini Coefficients. The data that is collected will range from 2011 and 2022. Data from 2022 was the most recently posted data available in each of the six New England states.

4.2 Empirical Model

Following Fawaz et al. (2015), this study has adjusted their logistic regression model. In this model, we have added the following independent logistic variables by state: unemployment rate reported monthly by state, labor force participation rate by state, welfare spending by each New England state, and the Top 1% wealth share.

$$\text{Ln-Gini}_i = \beta_0 + \beta_1(\text{Ln-UR}_{State}) + \beta_2(\text{Ln-LFPR}_{State}) + \beta_3(\text{Ln-Welfare Spending}_{State}) + \beta_4(\text{Ln-T1\% Wealth Share}) + \varepsilon_i$$

Ln-Gini$_i$ is the annual reported index for income inequality by state. The index ranges from 0 (perfect inequality) and 1 (perfect inequality) and is reported on an annual basis by year. *Ln-UR*$_{State}$ is the unemployment rate reported monthly by each of the six New England States. Similarly, *Ln-LFPR*$_{State}$ is also reported monthly by state. The final two variables that are translated into their natural log form are welfare spending by state and the top 1% wealth share by state. The top 1% wealth share is the average share per month based on value of assets. Finally, welfare spending data is collected from an independent website that tracks how much each state spends on welfare per month between 2011 and 2022.

5.0 EMPIRICAL RESULTS

In our empirical results, one of the main takeaways came from the unemployment data. No matter the impact, positive or negative, the change in the unemployment rate has very little impact on income inequality between all six New England states. On the other hand, an increasing Labor Force Participation Rate decreases the Gini index to all states that the variable is significant. Another large standout is that Massachusetts is one of two states that experiences increasing inequality from welfare spending (the other state being Maine). We also analyzed the share of wealth distribution and the impact it would have on each state's respective Gini coefficient. Based on our results, we found that an increasing top 1% wealth share decreases income inequality in three states to which the variable can describe the Gini index (Massachusetts, New Hampshire, and Vermont). The only state that was negatively impacted by a growing wealth share of the top 1% was Rhode Island.

Rhode Island and Maine were the two states in the region that had less than two variables in our model that could describe their respective Gini coefficients. One important note from this is that both Rhode Island and Maine had the two lowest Gini coefficient variations compared to other New England states. After finding this, we conducted additional research into the population density for each state. It was found after the fact that Rhode Island and Maine were ranked in the top five most and least condense states respectively (as of 2022).

Another crucial finding is that Vermont was the only New England state that had all four variables present in the model be significant (in addition to the intercept). Finally, New Hampshire was the only state that was negatively impacted by the growing labor force participation rate, but is also the only state that was positively impacted by less welfare spending and less share from the top 1% .

Despite the positive results that came from our empirical model, there are a few limitations that should be noted from our research. First, a relevant portion of the data comes from the U.S. Census Bureau which could likely lead to a lack of reported data or even misreported data. As previously mentioned, our data ranged from 2011 to 2022. Knowing that this data was reported on a monthly basis, perhaps the amount of observations we collected (144) was too little to come up with an accurate model. Additionally, the selected variables could have also been a reason why our results were not consistent with each state. Finally, the timeline our data was collected was through the pandemic (2020-2022) which could also result in the possibility that our data could have been skewed from this.

For those looking to advance research in this field, perhaps it would be optimal to consider other macroeconomic variables when building a new model. It would also be worth while to consider expanding the studied states (i.e., east coast, west coast, entire nation?). No matter the new approach, the opportunity to expand research in this field is growing with new availability of data.

5.1 CONCLUSION

Based on our findings, we can conclude that Rhode Island and Maine's Gini index could only be described by the top 1% wealth distribution and welfare spending, respectively. In terms to the welfare spending, a larger budget in welfare spending yields a greater Gini index or yields greater income inequality. As previously mentioned, Massachusetts the largest welfare budget over the 12-year spans the data was collected and based on the results from our logistic regression model, we found that Massachusetts' Gini index was severely impacted the most among other New England states. The final major takeaway from this research was the little impact unemployment had on the Gini index. Even in states to which the variable was significant, changing unemployment rate had very little impact on the Gini index in each state in the New England region. Continuing research in this field should consider expanding the model presented in this paper to a larger demographic sample size. With that, this area of research has considerably a lot of potential to expand and find many breakthroughs to explain the current state of income inequality not only within regions, but in larger demographic areas as well.

Appendix A: Variable Description and Data Source

Acronym	Description	Data source
$LFPR_{State}$	Monthly reported labor force participation rate by state	St. Louis Fred Data
UR_{State}	Monthly reported unemployment rate data by state	St. Louis Fred Data
Welfare $Spending_{State}$	Monthly reported welfare spending data by state between 2011 and 2022.	Independent website for tracking government expenditures
T1% Wealth Share	Aggregate for individuals who reside in the top 1% (assets, income: net worth).	World Bank

Appendix B- Variables and Expected Signs

Acronym	Variable Description	What it captures	Expected sign
$LFPR_{State}$	Monthly reported labor force participation rate by state	St. Louis Fred Data	+
UR_{State}	Monthly reported unemployment rate data by state	St. Louis Fred Data	-
Welfare $Spending_{State}$	Monthly reported welfare spending data by state between 2011 and 2022.	Independent website for tracking government expenditures	-
T1% Wealth Share	Aggregate for individuals who reside in the top 1% (assets, income: net worth).	World Bank	-

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