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Addressing Health Disparities by Modeling the Determinants of Income Inequality

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ABSTRACT
Income inequality is a measure of how unequal a country's income distribution is in any given year. Although it is generally associated with developing countries, the United States happens to have one of the highest levels of inequality of any industrialized country. While there are many competing theories as to what the primary drivers are, this paper examines some of the key determinants of inequality and further explores its established relationship with health and social problems. By developing a robust ordinary least squares (OLS) regression model, this study can serve as a template for addressing income inequality and reducing health and social problems.

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Introduction
In 2013, President Obama described income inequality as the "defining challenge of our time." In a country where 85.1% of all new income went to the top one percent during the post-2008 recession recovery [1]. the former President's words were sobering and warranted. In the years since, little has been done to address this, leaving many wondering: what caused this and what can we do to fix it? The objective of this paper is to further address this by presenting an alternative model for describing income inequality in the United States and evaluating how policy changes drive meaningful improvement in health equity.

Income and wealth inequality are topics that have been studied and debated by the economic and political communities for decades. One of the first major developments in this field was the development of a tool to measure inequality, called the Gini coefficient. Published by statistician and sociologist Corrado Gini, the Gini coefficient measures the income distribution of a nation's residents – from perfect inequality to perfect equality [2]. Since then, researchers have attempted to explain the movements in the coefficient using numerous different inputs.

One of the most prominent theories was developed by French economist Thomas Piketty. In his seminal book, Capital in the Twenty-First Century, Piketty posits that the rate of return on capital (dividends, stock market returns, rental income, interest income) is greater than that of economic growth over time [3]. This inherently leads to a self-sustaining cycle where wealthy people with resources profit off high-yield assets, while poorer people remain left out. Piketty argues that excessive inequality can only be fixed with government intervention, primarily through a tax increase on the wealthiest individuals. This sentiment is shared by many progressive scholars, including Paul Krugman, Gabriel Zucman, Emmanuel Saez, and Robert Reich.

Another renowned economist that shares strong concerns about the rising levels of inequality is Nobel Prize winner Joseph Stiglitz. He argues that the primary driver is the value of urban land and housing, a sentiment shared by Matthew Rognolie [4]. During waves of banking deregulations, for example, rather than lending money for creating new businesses, banks channeled their resources towards fixed assets like buildings and real estate. Coupled with increasing demand for homeownership in urban cities, they posit that inequality is driven primarily by real estate values and not returns on capital stock. Stiglitz believes that to counteract the self-perpetuating inequality cycle, we need to advocate for raising the minimum wage, stronger anti-trust laws, and higher capital gains tax rate [5].

These existing theories, among others, have helped to develop a framework for capturing the determinants of income inequality in a simple and statistically significant method. In addition to these variables, regressions involving a number of other variables were also tested, including, capital performance, homeownership levels, tax rates, minimum wage, political affiliations, real GDP, consumer debt, cost of college, and others. The purpose of testing these variables is to create a model that can explain the drivers and variations in the Gini coefficient, without having autocorrelation or multicollinearity issues.

Health Disparities
Understanding the drivers of inequality is an important step towards reversing it in the United States today. The concern of many economists and politicians is that excessive inequality leads to poor health outcomes, constrained social mobility, low education

levels, and corruption. This is borne out of extensive research on the ramifications of inequality within and between countries, with studies showing those with greater inequality experiencing significantly more health and social problems – including lower life expectancy, higher infant mortality, lower education levels, higher prevalence of substance use, greater levels of imprisonment, lower social mobility, and higher homicide rates [6].

Income inequality has been shown to have both an indirect and direct effect on medical and psychosocial problems. One of the most likely implications of income inequality relates to people's anxiety about their status [7]. By participating in a hierarchical society like the United States, people's competition for status and resources lead to a chronic state of "status anxiety". Numerous studies have confirmed this assertion, with findings demonstrating that people of lower socio-economic status in more equal countries tend to do better than those in lower socio-economic groups in more unequal countries [8].

Furthermore, a study by Lopez et al. determined that income inequality was associated with higher medical costs, with every one percent increase in the Gini coefficient of a county leading to a $40K increase in annual Medicare costs, increase of 175 Medicare inpatient days, and higher rates of preventable admissions. Other studies have also reported negative associations with depression, self-rated health, and environmental air quality. Moreover, even the few healthcare providers and resources that are available in poorer communities are cost-prohibitive due to high insurance premiums, exorbitant out-of-pocket expenses, or underinsurance. These factors culminate in a predicted difference in life expectancy of 10-15 years between the wealthiest and poorest Americans [9-14].

Methodology

After conducting a comprehensive series of statistical analyses and evaluating multiple models, the following equation 1 emerged as the most statistically significant and representative of the data:

$$Y = \beta_0 + \beta_1\, SP500 + \beta_2\, Union + \beta_3\, Poverty + \varepsilon$$

The dependent variable, Y, is the Gini coefficient. As briefly highlighted earlier, this coefficient captures the income distribution of a country's residents. It ranges between 0 and 1, representing perfect equality and perfect inequality, respectively. According to the Census Bureau, the Gini coefficient last year in the United States was 0.479 – which is surprisingly high for a wealthy, industrialized country after the period of mass-urban migration. The first independent variable, SP500, represents the annual stock price for the Standard & Poor's 500 index. This variable is based on the market cap for the 500 largest publicly traded companies and is one of the best representations of the U.S. stock market performance. The purpose of this variable was to capture the elements ascribed by Thomas Piketty, particularly the returns on capital investments. Investing in the S&P500 or the individual stocks is an asset that is only available to the wealthiest Americans. Thus, incorporating this variable was one way to capture the superior returns from the stock market, and determine whether Piketty's arguments on capital investments are valid. The expected sign of the coefficient is positive, since it is assumed that increases in stock value will result in higher inequality.

The next independent variable, Union, represents the percentage of each state's nonagricultural employees who are union members. In the last few decades, union rates have dropped significantly– from over 20% to under 10%. This means less collective bargaining power for lower-wage employees, giving them virtually no leverage to advocate for higher wages, improved working conditions, and stronger benefits. Robert Reich, former labor secretary under President Clinton and professor of public policy at UC Berkeley, asserts that labor unions are an integral part of a fair society. Just as how increases in the S&P500 resulted in positive benefits for wealthy people, reducing union rates results in negative benefits for the lower and middle classes. Thus, the expected sign of the coefficient is negative, since lower union rates will result in higher inequality.

The final independent variable, Poverty, represents the annual poverty level in the United States. Although poverty and inequality are often conflated, they are not equivalent. While it is generally agreed upon by economists that inequality can lead to poverty through wealth distributional patterns that favor the wealthy, my contention is that the opposite could also be true: poverty could potentially exacerbate inequality. In the last decade, for example, Americans witnessed the effects of a recession on many working-class people. Overnight, millions went from living in comfortable homes, sending their children to high-quality schools, and having robust 401k's, to owning virtually nothing and relying on the government for their survival. Income inequality did not reduce them to their current levels of poverty, but rather their abysmal circumstances. Coupled with the lack of opportunities, people living below the poverty line remain trapped and can't get out. As discussed earlier, the overwhelming majority of economic gains following the recession went to the top income earners. While those in poverty have trouble getting back on their feet, those at the top continue to perform tremendously well; this dichotomy is likely why it is a significant variable in explaining the effects on inequality. Thus, the expected sign of the coefficient is positive, given that higher poverty levels is indicative of more people struggling to generate new income while those at the top continue to grow wealthier.

Data and Results

The time-series data for this study spans across five decades (1967-2015) and comes from the following sources: Gini coefficient from the Census Bureau, adjusted S&P500 values from the Shiller database, union rates from the Monthly Labor Review, and poverty levels from the Census Bureau. Descriptive statistics for the model depicted above are presented in Table 1. The descriptive statistics are broken down into several key characteristics: mean, median, and standard deviation. These reveal how the data is distributed and concentrated, along with how spread out the data is from the expected sample value.

Table 1: Descriptive Statistics for Equation 1

	Mean	Median	Standard Deviation
Gini Coefficient	0.436	0.432	0.0309
Poverty	33,618,060	33,642,000	6,689,791
Union Membership	18.20 %	16.3 %	5.79 %
S&P500	$ 937.61	$ 707.53	$ 538.94

Table 2 presents the Ordinary Least Squares regression results for the final model variables. They were selected because they are the autocorrelation-adjusted statistically-significant variables, with a compelling Durbin-Watson value of 1.79. Furthermore, since the model generated significant t-statistics, the multicollinearity was not significant enough to warrant overhauling the model (see Table 3 for multicollinearity test of all variables in this study). The signs perform as expected with relation to the Gini coefficient, with a negative relationship between union membership rates and positive relationships between financial markets and poverty. These variables were significant to under 0.1%, signifying a 99.9% chance that there won't be a Type 1 error. Additionally, the strong adjusted R^2 value of 0.903 signifies that the variables employed in the model accurately explain the movement in Gini without artificially inflating the model with excessive variables.

Table 2: Ordinary Least Squares Regression Results for the Final Model Variables

	β	Standard Error	t-value	Significance*
Constant	0.439	0.019	22.77	5.59E-26
SP500	1.35E-5	3.0E-6	4.391	7.0E-5
Union	-3.07E-3	4.47E-4	-6.868	1.78E-8
Poverty	1.21E-9	3.25E-10	3.708	5.82E-4

*All variables are significant at 1%

R^2=0.911
Adjusted R^2=0.903
Durbin Watson=1.790
n=49;DOF=45

$$\widehat{Gini} = 0.439 + (1.35 * 10^{-5})SP500 - (3.07 * 10^{-3})Union + (1.21 * 10^{-9})Poverty$$

As the model shows, the union membership rate had the greatest marginal impact on income inequality out of all the variables tested. For every 1% decrease in unions, there was a corresponding 0.00307 raise in the Gini coefficient. Since 1967, union rates have dropped by 17% - leading to a rise in the Gini coefficient by 0.052. Considering that the Gini coefficient increased from 0.386 to 0.479 in that same time interval, union rates account for approximately half of that change. The original model included both the union rate and the inflation-adjusted minimum wage; however, it was evident that the variables were taking explanatory power away from each other, as exemplified by their high correlation coefficient of r = 0.88. In addition, this was consistent with labor economic theory, since fewer unions' means less collective bargaining power, thereby suppressing wages and benefits for the lower-wage workers.

The next largest marginal impact was from the S&P500. For every $100 increase in the index, there was a corresponding 0.00135 raise in the Gini coefficient. Since 1967, the S&P500 has more than tripled (adjusted for inflation), gaining approximately $1500; according to the model, this led to a rise in the Gini coefficient by 0.0203. This accounts for about 20% of the change in the Gini in the last half century. One of the variables that had strong multicollinearity issues with the S&P500 data was real GDP. After running the regression with both variables included (see Table 4 in Appendix), it became evident that S&P500 was statistically-significant while real GDP was not.

The final variable tested was the poverty level. For every 1,000,000 more people living in poverty, there was a corresponding 0.00121 raise in the Gini coefficient. Since 1967, the poverty level has risen by more than 15 million people, leading to an increase in the Gini coefficient by 0.0181. Similar to the S&P500, this accounts for about 20% of the change in the Gini over the course of the last fifty years. As with the other independent variables used, the poverty data had significant multicollinearity issues with other potential data. The original model also included accumulated consumer credit debt; however, it was removed after testing both t-values and determining that poverty was the superior metric.

Summary and Conclusion

The Ordinary Least Squares regression model has shown that capital markets, union rates, and poverty, are key determinants for the Gini coefficient in the United States. These variables performed as expected: capital markets and poverty are positively related to Gini, while union membership is negatively related. The data reinforces Piketty's belief that capital investments generate higher returns, thereby creating a system where people with resources benefit more financially than those without. Furthermore, the model corroborates Reich's argument that unions (minimum wage by association) play a major role in inequality, since they provide a platform for low and medium wage workers to advocate for higher pay to close the income gap. On the other hand, there was a lack of significance between homeownership rates and inequality in the core model, clearly counteracting the assertions made by Rognolie and Stiglitz (see Table 5,6 in Appendix). While there may be some correlation between the two, it is unlikely that real estate is a major causal mechanism for income inequality.

Given that one of the major drivers behind healthcare inequality is income inequality, the purpose of this study has been to focus on understanding the causes of the income gap and providing possible solutions for policymakers to address this at the root cause. The robust statistical model tested here has shown that the following policies can be beneficial to counteracting the downstream impacts of income inequality: raising capital gains tax rates on investment incomes, increasing taxes on wealthier Americans, advocating for labor unions and increasing wages, and improving access to resources for people in poverty.

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Table 3: Autocorrelation Adjusted Core Model

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.955	.911	.903	.004	1.790

The Cochrane-Orcutt estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	.008	3	.003
Residual	.001	44	.000

The Cochrane-Orcutt estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
SP500	1.346E-5	.000	.246	4.391	.000
Union Membership	-.003	.000	-.578	-6.868	.000
Poverty	1.206E-9	.000	.271	3.708	.001
(Constant)	.439	.019		22.771	.000

The Cochrane-Orcutt estimation method is used.

Table 4: Autocorrelation Adjusted Model with Housing

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.956	.914	.904	.004	1.865

The Cochrane-Orcutt estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	.008	4	.002
Residual	.001	43	.000

The Cochrane-Orcutt estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
SP500	1.140E-5	.000	.209	3.306	.002
Union Membership	-.003	.000	-.539	-6.031	.000
Poverty	1.259E-9	.000	.283	3.862	.000
Homeownership Rate	.001	.001	.084	1.268	.211
(Constant)	.337	.083		4.082	.000

The Cochrane-Orcutt estimation method is used.

Note: Incorporating homeownership rate, as prescribed by Rognolie and Stiglitz, is a statistically-insignificant variable in an otherwise robust model.

Table 5: Autocorrelation Adjusted Model with RGDP

Model Fit Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.956	.914	.904	.004	1.757

The Cochrane-Orcutt estimation method is used.

ANOVA

	Sum of Squares	df	Mean Square
Regression	.008	4	.002
Residual	.001	43	.000

The Cochrane-Orcutt estimation method is used.

Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
SP500	1.135E-5	.000	.207	3.034	.004
Union Membership	-.003	.001	-.487	-3.909	.000
Poverty	1.088E-9	.000	.244	3.153	.003
RGDP ($)	1.244E-15	.000	.145	.993	.326
(Constant)	.425	.024		17.609	.000

The Cochrane-Orcutt estimation method is used.

Note: Incorporating real GDP or (real GDP)^2 is a statistically-insignificant variable in an otherwise robust model

Table 6: Multicollinearity Test - Correlation Coefficients for all Possible Variables

		Poverty	Unemp. Rate	Corp. Profits	Union	Top Tax	Debt	RGDP	Republican	Home	SP500	Min. Wage	College	Lowest Tax	Insurance
Poverty	Pearson Correlation	1	.383**	.836**	-.867**	-.778**	.879**	.866**	-.301*	.335*	.596**	-.659**	.832**	-.568**	.191
	Sig. (2-tailed)		.006	.000	.000	.000	.000	.000	.034	.017	.000	.000	.000	.000	.184
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Unemp. Rate	Pearson Correlation	.383**	1	.146	-.164	-.120	.172	.102	.045	-.062	-.298*	-.027	.083	-.278	-.273
	Sig. (2-tailed)	.006		.313	.255	.408	.233	.480	.757	.668	.036	.853	.566	.050	.055
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Corp. Profits	Pearson Correlation	.836**	.146	1	-.767**	-.569**	.978**	.915**	-.295*	.481**	.781**	-.493**	.971**	-.687**	.007
	Sig. (2-tailed)	.000	.313		.000	.000	.000	.000	.038	.000	.000	.000	.000	.000	.959
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Union	Pearson Correlation	-.867**	-.164	-.767**	1	.918**	-.832**	-.937**	.150	-.562**	-.726**	.878**	-.770**	.502**	-.144
	Sig. (2-tailed)	.000	.255	.000		.000	.000	.000	.298	.000	.000	.000	.000	.000	.318
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Top Tax	Pearson Correlation	-.778**	-.120	-.569**	.918**	1	-.655**	-.786**	-.003	-.404**	-.558**	.924**	-.592**	.368**	-.303*
	Sig. (2-tailed)	.000	.408	.000	.000		.000	.000	.983	.004	.000	.000	.000	.009	.033
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Debt	Pearson Correlation	.879**	.172	.978**	-.832**	-.655**	1	.959**	-.281*	.540**	.809**	-.562**	.980**	-.687**	.096
	Sig. (2-tailed)	.000	.233	.000	.000	.000		.000	.048	.000	.000	.000	.000	.000	.507
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
RGDP	Pearson Correlation	.866**	.102	.915**	-.937**	-.786**	.959**	1	-.221	.653**	.852**	-.727**	.918**	-.614**	.132
	Sig. (2-tailed)	.000	.480	.000	.000	.000	.000		.123	.000	.000	.000	.000	.000	.363
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Republican	Pearson Correlation	-.301*	.045	-.295*	.150	-.003	-.281*	-.221	1	.068	-.251	-.114	-.317*	-.125	-.118
	Sig. (2-tailed)	.034	.757	.038	.298	.983	.048	.123		.638	.078	.431	.025	.388	.416
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
Homeownership	Pearson Correlation	.335*	-.062	.481**	-.562**	-.404**	.540**	.653**	.068	1	.638**	-.461**	.440**	-.426**	.205
	Sig. (2-tailed)	.017	.668	.000	.000	.004	.000	.000	.638		.000	.001	.001	.002	.152
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50
SP500	Pearson Correlation	.596**	-.298*	.781**	-.726**	-.558**	.809**	.852**	-.251	.638**	1	-.530**	.825**	-.407**	.132
	Sig. (2-tailed)	.000	.036	.000	.000	.000	.000	.000	.078	.000		.000	.000	.003	.355
	N	50	50	50	50	50	50	50	50	50	51	50	50	50	51
Min. Wage	Pearson Correlation	-.659**	-.027	-.493**	.878**	.924**	-.562**	-.727**	-.114	-.461**	-.530**	1	-.500**	.356*	-.210
	Sig. (2-tailed)	.000	.853	.000	.000	.000	.000	.000	.431	.001	.000		.000	.011	.143
	N	50	50	50	50	50	50	50	50	50	50	50	50	50	50