January 2015

The Effects Of Income Inequality On Society

Jessica Lee Clark

THE EFFECTS OF INCOME INEQUALITY ON SOCIETY

by

Jessica Lee Clark
Bachelor of Arts, the College of Saint Benedict, 2008
Master of Science, the University of North Dakota, 2015

A Thesis

Submitted to the Graduate Faculty

of the

University of North Dakota.

in partial fulfillment of the requirements

for the degree of

Masters of Science in Applied Economics

Grand Forks, North Dakota
May
2015

This thesis, submitted by Jessica Clark in partial fulfillment of the requirements for the Degree of Master of Science in Applied Economics from the University of North Dakota, has been ready by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

Xiao Wang

Xiao Wang

Prodosh Simlai

Prodosh Simlai

Kwan Yong Lee

This thesis is being submitted by the appointed advisory committee as having met all of the requirements of the School of Graduate Studies at the University of North Dakota and is hereby approved.

Wayne Swisher

Wayne Swisher
Dean of the School of Graduate Studies

May 7, 2015

Date

PERMISSION

Title The Effects of Income Inequality on Society

Department Applied Economics

Degree Master of Science in Applied Economics

In presenting this thesis in partial fulfillment of the requirements for a graduate degree from the University of North Dakota, I agree that the library of this University shall make it freely available for inspection. I further agree that permission for extensive copying for scholarly purposes may be granted by the professor who supervised my thesis work or, in her absence, by the chairperson of the department or the dean of the School of Graduate Studies. It is understood that any copying or publication or other use of this dissertation or part thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the University of North Dakota in any scholarly use which may be made of any material in my thesis.

Jessica Clark
May 1st, 2015

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I wish to express my sincere appreciation to the members of my advisory committee for their guidance and support during my time in the master's program at the University of North Dakota. I would especially like to thank Dr. Xiao Yang, whose support and insight during the process of my research was invaluable. Finally, I would like to thank my husband and family. Your support and encouragement made it possible for me to be where I am today.

ABSTRACT

This study is an examination of the relationship between income inequality and numerous indicators that capture the physical health of the citizens, additionally controlling for numerous other confounding factors. The analysis contributes to the literature by examining this relationship at a more disaggregated level within the Unites States than previous studies. This approach may help us to explore any impacts of income inequality on health that are lost in aggregation. The analysis also includes the most recent recession and adds to the literature the impact of inequality on health during a period of economic crisis. Results suggest that there is a strong relationship between income inequality and health indicators at the U.S. county level, and that the health of American citizens is negatively affected by increasing disparities in income. Even when controlling for the economic recession, income per capita, population density, and the unemployment rate, this relationship is still significant.

CHAPTER I

INTRODUCTION

Income inequality is perhaps the greatest economic issue of our time. Both nationally and internationally, this topic has garnered an increasing amount of attention in recent years. In the United States, income inequality has steadily been on the rise since the 1970s, and has seen huge increases in the last twenty years (Alvaredo et al, 2013). As of 2013, the top 1 percent of American households earned 18 percent of all pre-tax income (Alvaredo et al, 2013). As of 2010, the top 1 percent of American households owned 35 percent of the country's private wealth. This is more than the wealth of the bottom 90 percent combined (Allegretto, 2011). Similarly, as of 2007, the top 1 percent of American households owned 38 percent of all stock market wealth, and the top 10 percent of American households owned 81 percent of all stock market wealth (Allegretto, 2011). This is significant, as the increased wealth of the top 1 percent has had a noticeable effect on the overall income inequality in the United States (Atkinson, Piketty, and Saez 2011). These realities beg several questions. First, while a certain amount of income inequality is inevitable in a capitalist economy, at what point does income inequality begin to have a negative effect on society? And more specifically, within the United States, is the overall strength and health of society and its members weakened by increasing disparities in income?

In recent years, many studies have been devoted to examining the topic of income inequality. These studies have examined this issue across nations[3,6,13,15,23], within nations [16,17] and within the United States[6,7,8,9,10,11,12,14,20]. A number of studies have shown a correlation between income inequality and various health indicators, such as rates of mortality[8,9,10,12,13,14,16,17,19], diabetes mortality[20], and sexually transmitted diseases[7]. Many of these studies were conducted at the state[9,10,11,12] or national[22] level, or among metropolitan statistical areas (MSAs)[14]. However, it is not clear that these relationships hold at all levels of locality throughout the United States. MSAs, for example, are metro areas consisting of an urban center, and any adjacent counties that have a high degree of social and economic integration with that urban center. MSAs have, by definition, a population of 10,000 or more, and as such, do not account for rural areas.

Deaton (2003) examined in depth the literature addressing the effect of income inequality on health. After reviewing numerous of studies on the topic, his overall conclusion was that income inequality has a negative impact on health indicators, with an increased effect in developing countries. In these developing nations, the disparity between rich and poor constitutes large differences in living conditions. The poor have increased mortality rates because of inadequate sanitation, unhealthy working and living environments, poor nutrition, high rates of crime, among many others reasons. In many of these poor nations there is no social safety net to ensure a minimum standard of living. In contrast, we see smaller ranges of income inequality in rich nations. The distance between "have" and "have nots" is smaller. In rich countries, the poor still experience less favorable working and living environments, poor nutrition, and are often cannot escape from neighborhoods with high rates of crime; however the severity of these is diminished.

The main objective of this paper is to reexamine the relationship between income inequality and health at the United States county level, for the years 2006 to 2010. This time period includes the most recent economic recession, which began in December 2007 and ended in June 2009. The addition of this economic event will add to the depth of the analysis, as the effects of income inequality have not yet been examined for this time period.

Very few studies have examined the impact of income inequality at the U.S. county level. McLaughlin and Stokes (2002) and LaClere and Soobader (2000) examined this relationship using data from the late 1980s and early 1990s, 1988 to 1992 and 1989 to 1991 respectively. These studies are the only two published studies that have examined this relationship at the county level. In this current study, I will test the relationship between county-level income inequality and health indicator data, from 2006 to 2010 at the U.S. county level, while additionally accounting for demographic and socioeconomic characteristics as well. Unlike McLaughlin and Stokes (2002) and LaClere and Soobader (2000), the data I use in my analysis is more recent and also includes the most recent economic recession. This is important, as income inequality was much higher in 2006-2010 compared to 1988-1992. Additionally, there have been large changes in income inequality in the United States throughout the 1990s and 2000s, and no currently published studies account for this in their analysis.

Additionally, my research will differentiate itself from the current literature by including a wider variety of variables than previous studies. McLaughlin and Stokes (2002) examined the influence of minority racial concentration on the relationship between inequality and mortality. I will also examine this relationship; however, I will include numerous other variables as well. LaClere and Soobader (2000) examined the effect of county-level income inequality on the self-reported health of Whites and Blacks in three age groups. Again, my research will also examine the relationship between income inequality and health, while including numerous other variables. This research will close a gap in the literature, and attempt to answer questions that had previously gone unanswered.

Based on the literature, my null hypothesis is that the relationship between income equality and health indicators is negative, and moderately strong. As referenced earlier, Deaton (2003) determined that income inequality has a negative impact on health indicators; with income inequality having a larger effect in developing nations. Put another way, we would expect the Gini coefficient to have an increased effect on health in poor nations, since the Gini coefficient value is higher for those nations. In contrast, for rich nations such as the United States, the Gini coefficient value is smaller, and thus we would expect a diminished impact on health indicators. Several studies have found that the effect of income inequality on health was substantially diminished after controlling for race, education, and individual income. This study controls for these variables, in addition to many others, and therefore, we also expect the effect of income inequality on health to diminish after controlling for these variables.

CHAPTER II

DATA AND METHODOLOGY

Due to the scarcity of county-level data in the United States, the data required for this analysis came from a variety of sources; all of which were U.S. federal government departments and agencies. Roughly one-third of the variables are from the 2006 – 2010 American Community Survey. Another one-third of the variables are from the Centers for Disease Control, with the remaining one-third of variables coming from the Department of Commerce, the Census Bureau, and the National Archive of Criminal Justice Data. All of the data sources have rigorous standards for data integrity, and because of this, we can be confident in the accuracy of the data.

The goal of this study was to find county-level data for the time period of January 1, 2006 to December 31, 2010, for each of these years individually. However, due to confidentiality constraints and a lack of annual data for some measures, the data was only available for the combined 2006 to 2010 time period for one of the four dependent variables, and four of the ten independent variables. In the case of infant mortality, divorce rates, and injury death dates, the data is only available at the county level in grouped time periods. This is due to confidentiality constraints, in order to protect personal privacy of people who live in counties with low populations. In the case of the Gini coefficient and education, this data is simply not gathered at the county level on an annual basis. Finally, due to a lag in the time between when the data is gathered and published, it was not possible to gather more recent data especially on such a wide variety of topics.

Table 1 summarizes the variables that were used in this study, provides a brief description, and also provides the data sources for those variables.

Table 1. Data Sources

Variable name	Variable Description	Data Source
Dependent Variables		
Mort	Age-Adjusted Mortality Rate	CDC Wonder, Mortality Data
Infant*	Infant Mortality Rate	CDC: National Center for Health Statistics
Diabetes	Diabetes Prevalence	CDC: Behavioral Risk Factor Surveillance System
STD	STD Rate	CDC: National Center for HIV/AIDS, Viral Hepatitis, STD, and TB Prevention (NCHHSTP)
Independent Variables		
Demographics		
Black	Percentage of population that is black	American Community Survey, 2006 - 2010
College*	Percentage of population with education attainment of college degree or above	American Community Survey, 2006 - 2010
Income		
Gini*	Gini Coefficient	American Community Survey, 2006 - 2010
Control Variables		
Family & Household Support		
Divorce*	Percentage of households with separation or divorce	American Community Survey, 2006 - 2010
Safety		
Crime	Violent, property and drug-related crimes per capita	National Archive of Criminal Justice Data
Injury*	Injury death rate	County Health Rankings & Roadmaps, CDC Wonder, Mortality Data
Physicians	Physicians per capita	U.S. Census Bureau
Robustness Check Variables		
Income	Income per capita, by state	U.S. Dept. of Commerce, Bureau of Economic Analysis
Popdensity	Population density, by state	U.S. Census Bureau, Census of Population & Housing
Unemployment	Unemployment rate	Bureau of Labor Statistics

Data is at the U.S. county level, unless otherwise noted.

* This data is for the combined period of 2006 – 2010, not for individual years within this period

The following four equations are the preliminary regressions that will be used in this study. These equations are based on the structure established by Deaton (2003). The dependent variables are the four health indicators we will be testing. The dependent variables are, in order of equation, the age-adjusted mortality rate, the infant mortality rate, the diabetes prevalence rate, and sexually transmitted disease (STD) cases per capita. The explanatory variables are, in order, percentage of population that is black, percentage of population with educational achievement of a college degree of higher, the rate of divorce/separation, the crime rate, the injury death rate, and physicians per capita, with ε_i as the error term. We have excluded the crime rate and the injury death rate from equations 3 and 4. This is appropriate, as these variables do not have an impact on diabetes prevalence or STD cases.

$$Mort_i = \beta_0 + (\beta_1 * Gini_i) + (\gamma_1 black_i + \gamma_2 college_i + \gamma_3 divorce_i + \gamma_4 crime_i + \gamma_5 injury_i + \gamma_6 physician_i) + \varepsilon_i \tag{1}$$

$$Infant_i = \beta_0 + (\beta_1 * Gini_i) + (\gamma_1 black_i + \gamma_2 college_i + \gamma_3 divorce_i + \gamma_4 crime_i + \gamma_5 injury_i + \gamma_6 physician_i) + \varepsilon_i \tag{2}$$

$$Diabetes_i = \beta_0 + (\beta_1 * Gini_i) + (\gamma_1 black_i + \gamma_2 college_i + \gamma_3 divorce_i + \gamma_4 physician_i) + \varepsilon_i \tag{3}$$

$$STD_i = \beta_0 + (\beta_1 * Gini_i) + (\gamma_1 black_i + \gamma_2 college_i + \gamma_3 divorce_i + \gamma_4 physician_i) + \varepsilon_i \tag{4}$$

Measures

In Table 2, are the summary statistics for the dependent and independent variables, broken down by category. All of the variables have 15,690 observations, with the exception of the age-adjusted mortality rate and crimes per capita. For the age-adjusted mortality, these observations were suppressed by the CDC due to confidentiality constraints. Mortality data is suppressed when the figure represents zero to nine lives. These small omissions comprise only one percent of the total observations, and as such, do not have a large impact on the overall analysis. For the crime rate, these missing observations are due to the fact that Florida does not report these statistics and neither do 93 percent of the counties in Illinois. These omissions comprise five percent of the total observations. Therefore, the relationship that is established between the crime rate and the dependent variables only applies to the portion of the United States that provided data.

Table 2. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variables					
Age-Adjusted Mortality Rate	15,497	838.35	154.58	100	2,332.7
Infant Mortality Rate	15,690	6.85	3.69	0	41.1
Diabetes Prevalence	15,690	9.95	2.15	3	19.8
STD Rate	15,690	3.15	3.24	0	42.4
Independent Variables					
Percentage Black	15,690	8.95	14.52	0	85.97
College Degree or Above	15,690	47.45	10.98	17.95	89.27
Gini Coefficient	15,690	0.432	0.04	0.207	0.645
Households with separation/divorce	15,690	12.93	2.75	1.60	26.93
Crimes per capita	14,880	0.99	0.62	0	7.9
Injury death rate	15,690	6,905.3	3,224.4	0	32,090
Physicians	15,690	0.15	0.20	0	6.21
Robustness Check Variables					
Income per capita, by state	15,690	36.99	4.53	27.92	71.22
Population density, by state	15,690	127,785	194,007	1015	8,848,868
Unemployment rate	15,690	6.12	3.19	0	29.1

The age-adjusted mortality rate is calculated as the mortality rate per 100,000 persons, using the 2010 census figures for the U.S. standard population. The infant mortality rate is the number of infant deaths per 1000 births. The diabetes prevalence rate is defined as the fraction of the population who has been diagnosed with diabetes. The STD rate captures the fraction of the population who were diagnosed with one of the following sexually transmitted diseases: gonorrhea, chlamydia, early latent syphilis, or primary and secondary syphilis. The STD rate has been modified from the original version, so that it now reflects the number of STD cases per 1,000 people. This is due to the fact that the STD rate is so low, that at a per person rate it was difficult to interpret constructively. The percentage black variable is the percentage of the population who identifies their primary race as black. The education variable captures the fraction of the population who has an associates, bachelors, masters, professional, or doctoral degree.

The Census Bureau defines the Gini index as "a statistical measure of income inequality ranging from 0 to 1. A measure of 1 indicates perfect inequality, i.e., one household having all the income and rest having none. A measure of 0 indicates perfect equality, i.e., all households having an equal share of income."[24] The equation for the Gini coefficient is as follows:

$$Gini = \frac{2}{\mu n^2} + \sum_{i=1}^{n} iX_i - \frac{n+1}{n}$$

where μ is the population mean, n is the weighted number of observations, and X_i is the weighted income of individual i, which is weighted by individual i's rank in the income distribution.[24] The Gini coefficient data was gathered from the 2006 – 2010 American Community Survey (ACS). The ACS surveys households in each month from January to December, and asks participants about income received during the previous 12 months. Each year's survey covers 23 months, from January of the previous year to November of the survey year. In total, the 5-year ACS used in this report covers the 71-month period from January 2005 through November 2010. Due to the way that this information is gathered, it was not possible to find the Gini coefficient by county for each year between 2006 and 2010. Ideally, we would hope to obtain Gini coefficient data for each county on an annual basis. Unfortunately, this data is not available. The second best option would be to obtain Gini coefficient data for each county in the United States for the year 2006. This data is also unavailable. The third best option, and the approach taken for this study, is to use Gini coefficient data for the time period of 2006 to 2010. This data is available at the county level for each year individually, and as such, allows us to draw conclusions about the effect of income inequality on health during this time period.

Throughout this paper, the phrase “a one-unit increase in the Gini coefficient” will be continually referred to in the interpretations of the regression results. It is important to understand what this implies. Since the Gini coefficient ranges from zero to one, with one indicating perfect inequality, and zero indicating perfect equality, a one unit increase in the Gini coefficient implies moving from an economy with perfect inequality to an economy with perfect equality. In the United States, for the time period of 2006 to 2010, the Gini coefficient ranges from 0.21 to 0.65. Therefore, we will never see a one-unit increase in the Gini coefficient in this study. However, it is referred to so that the real-world effects of changes in the Gini coefficient can be clearly understood. While the Gini coefficient may have a range of approximately 0.4 during this time period, there is no guarantee that it will not change in the future. By providing the impact of the Gini coefficient given a change from zero to one, it is then possible to calculate the impact of the Gini coefficient given any smaller range of movement.

In Figure 1, is a map of the Gini coefficient for all counties in the United States. There are distinct trends in the data. There is a horizontal band along the central part of the United States where income inequality is relatively low. This area of low income inequality also extends into the northern Midwest and Northeast. Additionally, there are small pockets of low income inequality counties in the Northwestern United States. We see most of the high income inequality counties in the South, although there are also small pockets in South Dakota. These pockets correlate almost exactly with counties that are completely encompassed by Native American reservations. There are also pockets of income inequality near large cities outside of the Deep South, such as Newark/New York City, Boston, Detroit, Chicago, Las Vegas, Los Angeles.

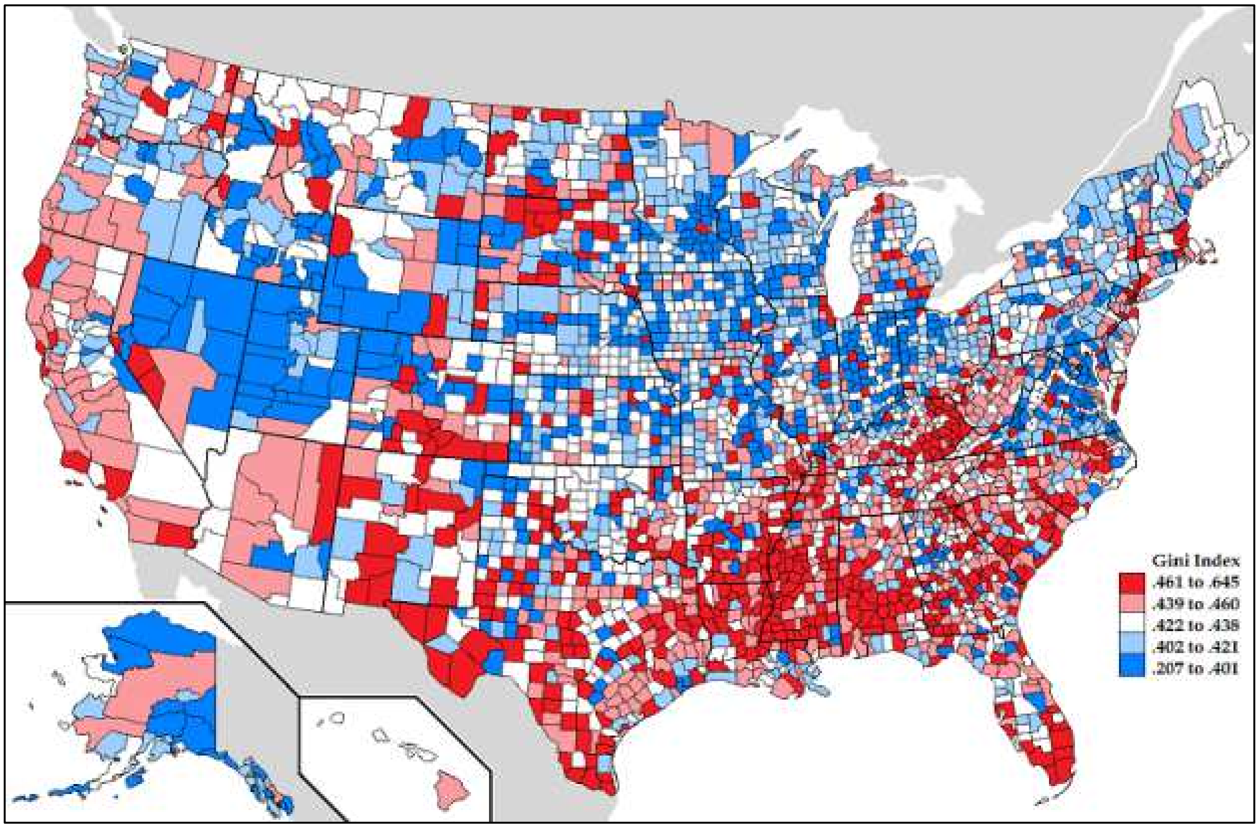

Figure 1: A Map of the Gini Coefficient by U.S. County

The fraction of households with separation or divorce was also gathered from the 2006 – 2010 American Community Survey. The crime rate is defined as the number of total crimes (violent, property, or drug-related) per capita. Similar to the age-adjusted mortality rate, the injury death rate is calculated as the injury mortality rate per 100,000 persons, using the 2010 census figures for the U.S. standard population. The data for physician per capita was gathered from the U.S. Census Bureau, and is based on information from the American Medical

Association's Physician Masterfile. Physicians are added to this registry when they enter accredited medical schools, upon entry into an accredited post-graduate residency training program, or when they obtain a license from a U.S. licensing jurisdiction.

The variables used in the robustness checks are income per capita, population density, and the unemployment rate. Income per capita was provided by the American Community Survey. The income per capita variable has been modified from the original version, so that it now reflects income per capita in thousands of dollars. For example, the income per capita of North Dakota in 2010 was $42,462. This has been modified so it now reads as 42.462, in thousands of dollars. This modification helps us more clearly interpret the results of the regression equations. Income per capita is derived by dividing the total income of people 15 years old and over in a geographic area by the total population in that area. In this case, the geographic areas are each individual U.S. state. It was necessary to gather this data at the state level in order to properly perform the robustness check. Similarly, population density data was gathered at the state level as well; for the same reason. The population density data was provided by the U.S. Census Bureau. Population density is calculated by dividing the total number of people living in a particular U.S. state by the total population in that state. Just like the income per capita variable, population density has also been modified into population density per thousand. In this case, it is population density as 1,000 people per square mile instead of 1 person per square mile. So a one unit increase in population density implies an increase of 1,000 people per square mile. Again, this helps us more clearly interpret the results of the regression equations. The unemployment rate was gathered from the Bureau of Labor Statistics. It is based on the results of the Current Population Survey (CPS), a sample of 60,000 American households.

Variable Correlations

Table 3 outlines the correlation between the main dependent and explanatory variables, for regression equation 1. As we can see, the Gini coefficient has a correlation of 25% with age-adjusted mortality. The fraction of the population who is black has a moderately strong positive correlation with mortality and the Gini coefficient, at 35% and 38% respectively. College education is negatively correlated with mortality. The correlation is somewhat strong, at 53%. The divorce rate and the injury death rate have a 46% correlation with age-adjusted mortality. For the latter, this is rather self-evident as one is comprised of the other. The correlation between crime rate and infant mortality is low, at 24%. The variable physicians per capita has a weak negative correlation with age-adjusted mortality at 14%. Income per capita has a 35% correlation with age-adjusted mortality, and is negatively correlated. Population density has a very weak negative correlation with age-adjusted mortality, at 3%. Lastly, the correlation between the unemployment rate and age-adjusted mortality is moderate, at 21%.

In Table 4, is the correlation between the main dependent and explanatory variables, for regression equation 2. As we can see, the Gini coefficient has a correlation of 19% with infant mortality. Of the four dependent variables, the Gini coefficient has the weakest correlation with the infant mortality rate. The fraction of the population who is black has a moderately strong positive correlation with infant mortality, at 33%. The fraction of the population who is black has a moderately strong positive correlation with the Gini coefficient, at 37%. This correlation is very similar to the correlations observed between these variables and age-adjusted mortality. College education is negatively correlated with infant mortality. The correlation is weak, at 21%. The divorce rate and the injury death rate also have a 21% correlation with the infant mortality rate. The correlation between crime rate and infant mortality is very low, at 14%. The correlation between physicians per capita and infant mortality is nearly non-existent, at 0.7%. In fact, the correlation between physicians per capita and all of the other variables is quite weak. Income per capita has a 15% correlation with age-adjusted mortality, and is negatively correlated. Population density has a very weak correlation with age-adjusted mortality, at 1%. And lastly, the correlation between the unemployment rate and age-adjusted mortality is weak, at 13%. Of the four dependent variables, the unemployment rate has the weakest correlation with infant mortality.

Table 3: Correlations, Regression Equation 1

	Mortality	Gini	Black	College	Divorce	Crime	Injury	Phys.	Income per Capita	Pop. Density	Unemp. Rate
Mortality	1										
Gini	0.2539	1									
Black	0.3522	0.3780	1								
College	-0.5325	-0.1019	-0.2105	1							
Divorce	0.4639	0.2245	0.2604	-0.3401	1						
Crime	0.2353	0.2624	0.3492	-0.0538	0.2897	1					
Injury	0.4635	0.1437	0.0705	-0.3102	0.3616	0.1135	1				
Physicians	-0.1388	0.2078	0.0556	0.3779	-0.0500	0.1722	-0.09	1			
Income per capita	-0.3522	-0.1319	-0.1550	0.3562	-0.2275	-0.032	-0.25	0.177	1		
Population density	-0.0294	0.0689	0.1202	0.0431	-0.0100	0.0739	-0.08	0.159	0.3796	1	
Unemployment rate	0.2149	0.1445	0.2297	-0.2995	0.2800	0.1628	0.23	-0.081	-0.161	0.0754	1

Table 4: Correlations, Regression Equation 2

	Infant	Gini	Black	College	Divorce	Crime	Injury	Phys.	Income per Capita	Pop. Density	Unemp. Rate
Infant	1										
Gini	0.1861	1									
Black	0.3321	0.3736	1								
College	-0.2145	-0.1001	-0.2128	1							
Divorce	0.2145	0.2219	0.2616	-0.3351	1						
Crime	0.1377	0.2599	0.3403	-0.0520	0.2750	1					
Injury	0.2191	0.1590	0.0843	-0.3152	0.3693	0.1167	1				
Physicians	0.0069	0.2093	0.0591	0.3717	-0.0430	0.1688	-0.07	1			
Income per capita	-0.1456	-0.1302	-0.1557	0.3570	-0.2223	-0.032	-0.25	0.1761	1		
Population density	0.0136	0.0718	0.1229	0.0394	-0.0041	0.0756	-0.06	0.1609	0.3768	1	
Unemployment rate	0.1262	0.1468	0.2332	-0.3018	0.2858	0.1614	0.242	-0.0744	-0.161	0.0791	1

In Table 5, is the correlation between the main dependent and explanatory variables, for regression equation 3. The Gini coefficient has a correlation of 28% with diabetes. The fraction of the population who is black has a strong positive correlation with diabetes, at 51%. This correlation is much higher for diabetes than it is for age-adjusted mortality and infant mortality. The correlation between the fraction of the population who is black and the Gini coefficient is very similar to the correlation observed between these variables and age-adjusted mortality, at 37%. College education is strongly negatively correlated with diabetes, at 60%. The divorce rate has a 35% correlation with diabetes. The variable physicians per capita has a weak negative correlation with age-adjusted mortality, at 16%. Income per capita has a 38% correlation with age-adjusted mortality, and is negatively correlated. Population density has a very weak correlation with age-adjusted mortality, at 0.7%. Lastly, the correlation between the unemployment rate and age-adjusted mortality is moderately strong, at 42%. Of the four dependent variables, the unemployment rate has the strongest correlation with diabetes.

In Table 6, is the correlation between the main dependent and explanatory variables, for regression equation 4. For equation 4, the Gini coefficient has a correlation of 39% with the STD rate. Of the four dependent variables, the Gini coefficient has the strongest correlation with the STD rate. The fraction of the population who is black has a very strong positive correlation with STDs, at 72%. College education is negatively correlated with mortality and this relationship is quite weak. The divorce rate has a 23% correlation with STDs. The variable physicians per capita has a weak correlation with the STD rate, at 14%. Similarly, income per capita also has a 14% correlation with age-adjusted mortality, and is negatively correlated. Population density has a very weak correlation with age-adjusted mortality, at 3.6%. And lastly, the correlation between the unemployment rate and age-adjusted mortality is weak, at 22%.

Table 5: Correlations, Regression Equation 3

	Diabetes	Gini	Black	College	Divorce	Phys.	Income per Capita	Pop. Density	Unemp. Rate
Diabetes	1								
Gini	0.2802	1							
Black	0.5134	0.3719	1						
College	-0.5993	-0.0882	-0.2113	1					
Divorce	0.3548	0.2231	0.2626	-0.3330	1				
Physicians	-0.1649	0.2197	0.0615	0.3768	-0.0416	1			
Income per capita	-0.3842	-0.1327	-0.1584	0.3499	-0.2120	0.1653	1		
Population density	0.0077	0.0706	0.1220	0.0414	0.0067	0.1574	0.3871	1	
Unemployment rate	0.4222	0.1394	0.2248	-0.2922	0.2762	-0.0740	-0.151	0.0802	1

Table 6: Correlations, Regression Equation 4

	STD	Gini	Black	College	Divorce	Phys.	Income per Capita	Pop. Density	Unemp. Rate
STD	1								
Gini	0.3909	1							
Black	0.7152	0.3719	1						
College	-0.0936	-0.0882	-0.2113	1					
Divorce	0.2342	0.2231	0.2626	-0.3330	1				
Physicians	0.1380	0.2197	0.0615	0.3768	-0.0416	1			
Income per capita	-0.1408	-0.1327	-0.1584	0.3499	-0.2120	0.1653	1		
Population density	0.0360	0.0706	0.1220	0.0414	0.0067	0.1574	0.3871	1	
Unemployment rate	0.2227	0.1394	0.2248	-0.2922	0.2762	-0.0740	-0.151	0.0802	1

CHAPTER III

RESULTS

Regression Results

I then estimate the four equations by Ordinary Least Squares (OLS) regression. The full results of the OSL regression estimation are reported in Table 7. The results in each column indicate the estimated regression coefficients on the four different health indicators: the age-adjusted mortality rate, the infant mortality rate, the diabetes prevalence rate, and the STD prevalence rate. All coefficients but two are statistically significant in influencing age-adjusted mortality, the infant mortality rate, diabetes prevalence rates and STD rates. The two exceptions are crime on infant mortality, and physicians per capita on the age-adjusted mortality rate. These regression results show that income inequality has a strong effect on these health indicators. For every unit increase in the Gini coefficient, we expect an approximately 273 additional deaths per 100,000 people per year, for age-adjusted mortality. For infant mortality, we expect an approximately 3.5 additional deaths per 1000 live births per year, for every unit increase in the Gini coefficient. For diabetes, we expect an approximately 5.4 additional diagnoses of diabetes per capita, for every unit increase in the Gini coefficient. And for STD rates, we expect approximately .011 additional cases of STDs per 1,000 people, for every unit increase in the Gini coefficient.

Table 7: Regression Results for the Effect of the Gini Coefficient on Health Indicators

	(1) Mortality	(2) Infant	(3) Diabetes	(4) STDs
Gini	273.01***	3.47***	5.40***	11.20***
	(29.20)	(0.86)	(0.36)	(0. 538)
Black	1.81***	0.069***	0.053***	0.148***
	(0.07)	(0.002)	(0.0009)	(0.001)
College	-4.82***	-0.035***	-0.094***	0.016***
	(0.10)	(0.003)	(0.001)	(0.002)
Divorce	10.03***	0.070***	0.62***	0.062***
	(0.40)	(0.012)	(0.005)	(0.007)
Crime	15.80***	-0.035		
	(1.71)	(0.049)		
Injury	0.013***	0.0002***		
	(0.0003)	(9.5e-06)		
Physicians	-8.24	0.68***	-0.25***	0.836***
	(5.29)	(0.16)	(0.07)	(0.101)
_cons	698.74***	4.33***	10.85***	-4.72***
	(14.09)	(0.42)	(0.17)	(0.26)
N	14,687	14,880	15,690	15,690
R^2	47.80	16.0	52.96	53.77
RMSE	112.7	3.42	1.47	2.2

Note: Standard errors in parentheses
= "* p<0.10 ** p<0.05 *** p<0.01"

Figure 2 shows the relationship between the age-adjusted mortality rate and income inequality levels. It demonstrates that as counties become more unequal, the age-adjusted mortality rate increases. It is important to note that since the Gini coefficient for each of these years is the average of the Gini coefficient over the entire period, any changes between years are solely attributable to differences in the age-adjusted mortality rate. In every year from 2006 to 2010, we can see a clear difference in the age-adjusted mortality rate between income inequality quartiles. In 2006, the difference in the mortality rate for the highest income inequality quartile compared to the lowest income inequality quartile was 102.12 per 100,000. This is 102 excess deaths per 100,000 people due to the difference in income inequality quartiles. In 2007, this difference was 105; in 2008 it was 94, in 2009 it was 95, and in 2010 this difference was 99. Therefore, for the period of 2006 to 2010, there were 496 excess deaths per 100,000 people, due to difference in income inequality quartiles.

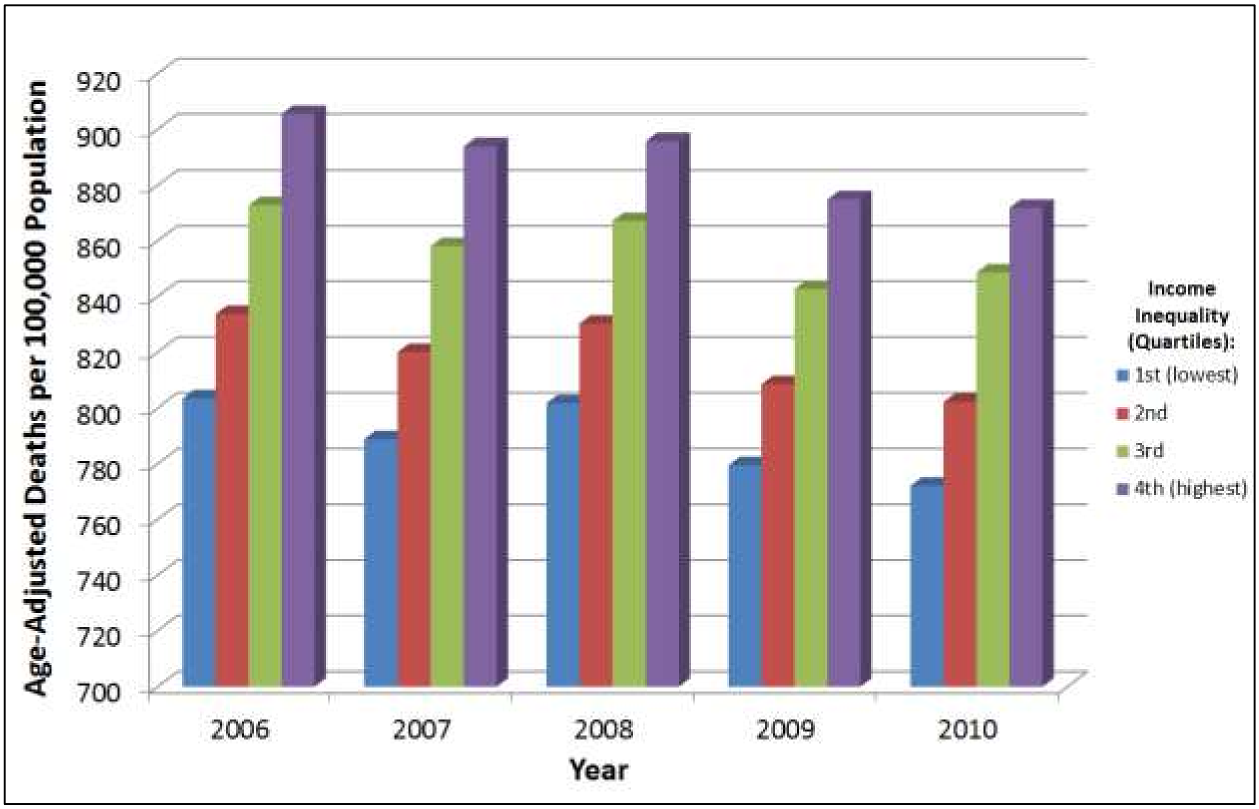

Figure 2: Income Inequality and Age-Adjusted Mortality, by Year

Figure 3 shows the relationship between diabetes prevalence and income inequality levels. It demonstrates that as counties become more unequal, the diabetes prevalence rate increases. While the difference in income inequality quartiles is not as pronounced for diabetes, was it was for age-adjusted morality, we can still see a distinct difference in diabetes prevalence rates between the quartiles. Diabetes prevalence rates increase slightly every year between 2006 and 2010. In 2006, the highest rate of diabetes per county was 10 percent but by 2010, it was

11.45 percent. We can see that diabetes prevalence is increasing overall during this time period. In 2010, the difference in the diabetes prevalence rate for the highest income inequality quartile compared to the lowest income inequality quartile was 1.5 percent. This is a 14.22 percent increase from lowest income inequality quartile to the highest.

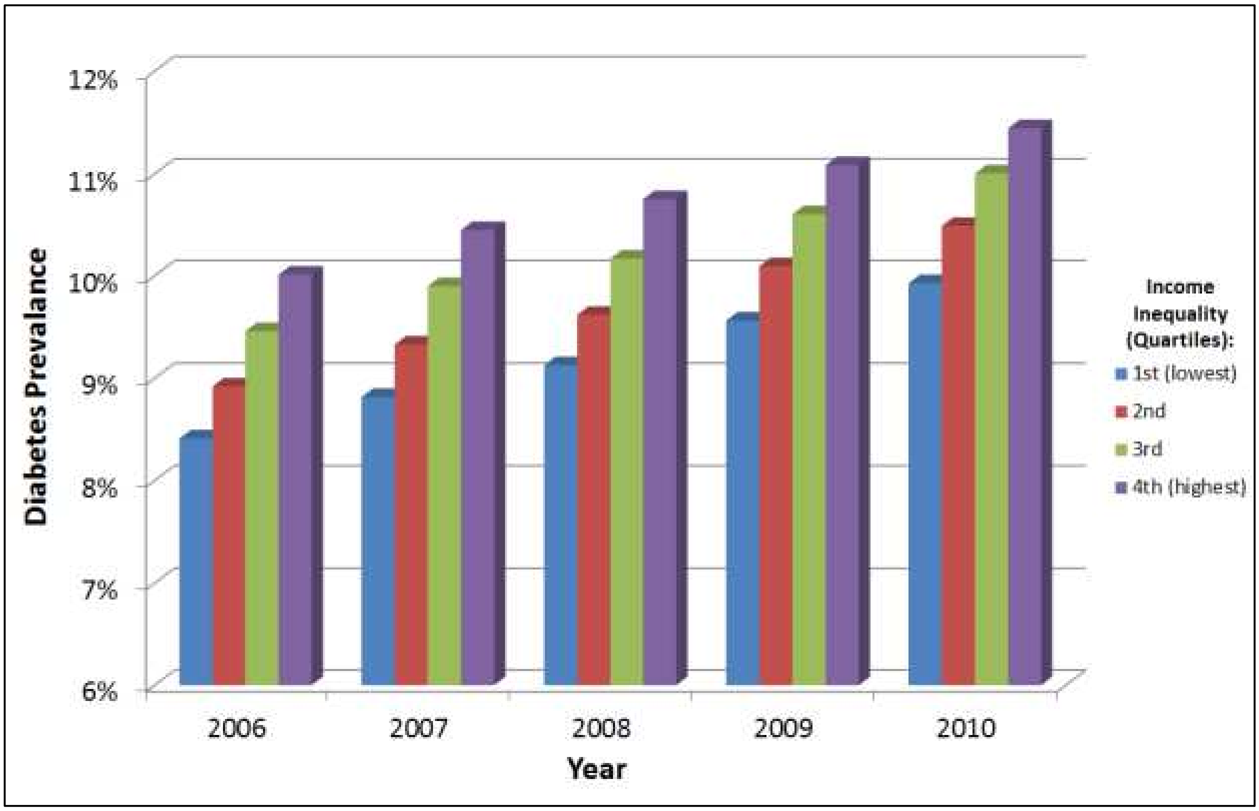

Figure 3: Income Inequality and Diabetes Prevalence, by Year

Figure 4 shows the relationship between the STD rate and income inequality levels. It demonstrates that as counties become more unequal, the STD rate increases dramatically. In every year from 2006 to 2010, we can see a clear distinction in the age-adjusted mortality rate, given the income inequality level. The most distinct difference is between the lowest income inequality quartile and the highest income inequality quartile. For each year from 2006 to 2009, the difference in the STD rate per 1,000 people for the highest income inequality quartile compared to the lowest income inequality quartile was 3.33. This is a 95 percent increase from lowest income inequality quartile to the highest. Similarly, there is a 59 percent increase from the highest income inequality quartile to the second highest income inequality quartile. This is a large increase in STD rates for a relatively small change in income inequality.

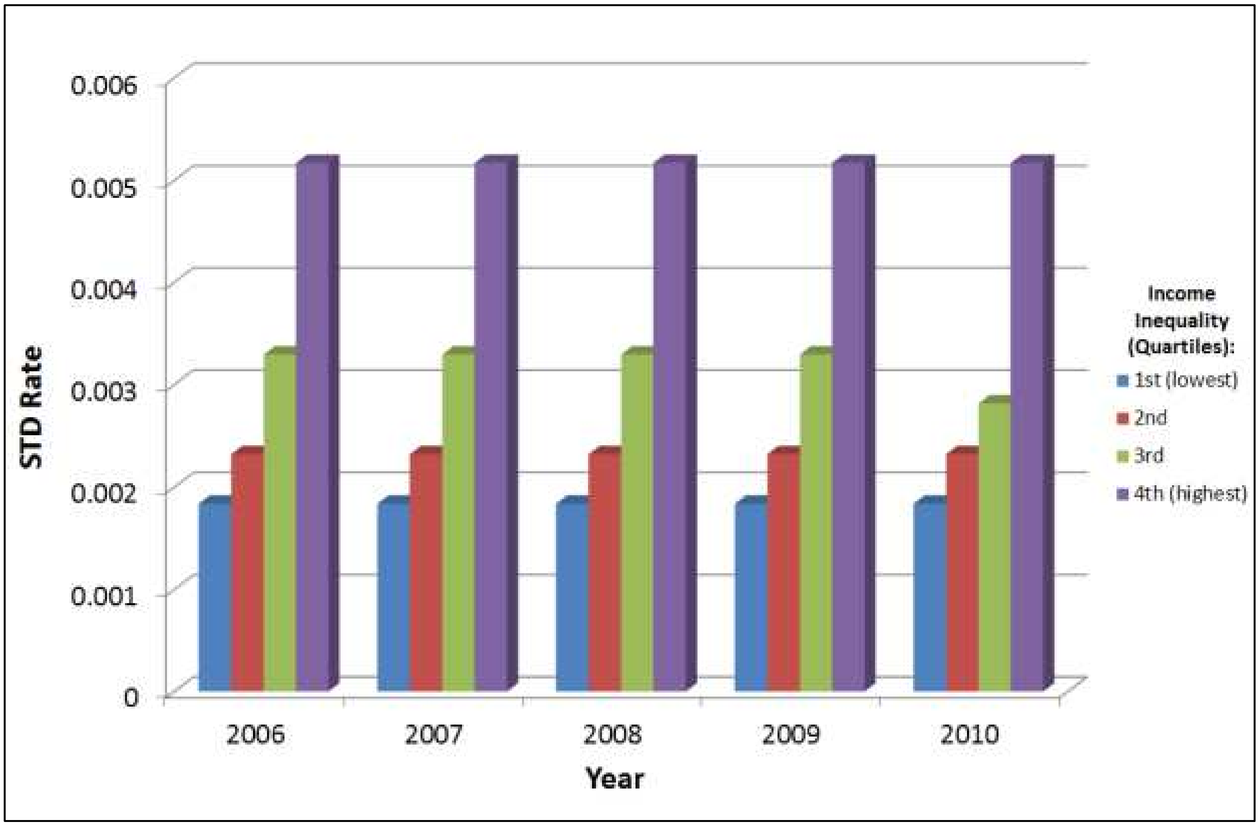

Figure 4: Income Inequality and STD Rates, by Year

State Fixed Effects Model

We then use a fixed effects model to explore the relationship between independent and outcome variables across states. Each state may have its own characteristics that influence the independent variables, and in using a fixed effects model, we can assess the net effect of the predictors on the outcome variables. State fixed effects partially controls for where people choose to live. Individuals who possess job skills that are in demand could choose to seek employment in more desirable areas to live. This could be geographic areas with better school, a stronger social safety net, perhaps better health outcomes, among many others attributes. In

Table 8 below, results from the initial regression equations are listed in columns labeled A, and results from the fixed effects model are listed in columns labeled B. As the regression results indicate, most of the parameter estimates and the statistical significance change only slightly. This is with the exception of the effect of income inequality on age-adjusted mortality and diabetes. After removing the influence of the individual states, for every unit increase in the Gini coefficient, we expect an approximately 131 additional deaths per 100,000 people per year, for age-adjusted mortality. This means the effect of income inequality on health indicators is roughly halved by controlling for state fixed effects. After removing the influence of the individual states, for every unit increase in the Gini coefficient, we expect an approximately 2.7 additional diabetes diagnoses. Similar to the state fixed effects for age-adjusted mortality, this is nearly half of the amount it was in the original regression. We can also see that controlling for state fixed effects has a minimal impact on the infant mortality rate, and STD rates per 1,000 people. The results also indicate that the fit of the model increases after controlling for state fixed effects. The R-squared value increases for each one of the four health indicator models.

Table 8: Regression Results from State Fixed Effect Models

	(1A) Mortality	(1B) Mortality	(2A) Infant	(2B) Infant	(3A) Diabetes	(3B) Diabetes	(4A) STDs	(4B) STDs
Gini	273.01***	131.5***	3.47***	3.30***	5.40***	2.74***	11.20***	10.34***
	(29.20)	(29.92)	(0.86)	(0.92)	(0.36)	(0.32)	(0. 538)	(0.537)
Black	1.81***	1.17***	0.069***	0.06***	0.053***	0.04***	0.148***	0. 16***
	(0.07)	(0.09)	(0.002)	(0.003)	(0.0009)	(0.001)	(0.001)	(0.0017)
College	-4.82***	-3.78***	-0.035***	-0.03***	-0.09***	-0.06***	0.016***	0.005**
	(0.10)	(0.11)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Divorce	10.03***	8.8***	0.070***	0.1***	0.62***	0.052***	0.062***	0.048***
	(0.40)	(0.42)	(0.012)	(0.01)	(0.005)	(0.004)	(0.007)	(0.007)
Crime	15.80***	25.0***	-0.035	0.13**				
	(1.71)	(1.82)	(0.049)	(0.055)				
Injury	0.013***	0.01***	0.0002***	0.0002***				
	(0.0003)	(0.0003)	(9.5e-06)	(9.90e-06)				
Physicians	-8.24	0.09	0.68***	0.78***	-0.25***	-0.36***	0.836***	1.49***
	(5.29)	(5.23)	(0.16)	(0.16)	(0.07)	(0.06)	(0.101)	(0.098)
_cons	698.74***	729.85***	4.33***	3.78***	10.85***	10.76***	-4.72***	-3.86***
	(14.09)	(14.71)	(0.42)	(0.45)	(0.17)	(0.16)	(0.26)	(0.264)
N	14,687	14,687	14,880	14,880	15,690	15,690	15,690	15,690
R^2	47.80	53.60	16.0	19.1	52.96	68.93	53.77	60.61
RMSE	112.7	106.46	3.42	3.36	1.47	1.2	2.2	2.04

Note: Standard errors in parentheses
= "* p<0.10 ** p<0.05 *** p<0.01"

Robustness Checks

The Great Recession

We then test whether the economic crisis had a noticeable effect on the relationship between the Gini coefficient and the four health indicators, using a fixed effects regression. We will do so using the following equations.

$$Mort_i = \beta_0 + (\beta_1 * Gini_i) + (\beta_2 * crisis) + (\gamma_1 black_i + \gamma_2 college_i + \gamma_3 divorce_i + \gamma_4 crime_i + \gamma_5 injury_i + \gamma_6 physician_i) + \varepsilon_i \tag{5}$$

$$Infant_i = \beta_0 + (\beta_1 * Gini_i) + (\beta_2 * crisis) + (\gamma_1 black_i + \gamma_2 college_i + \gamma_3 divorce_i + \gamma_4 crime_i + \gamma_5 injury_i + \gamma_6 physician_i) + \varepsilon_i \tag{6}$$

$$Diabetes_i = \beta_0 + (\beta_1 * Gini_i) + (\beta_2 * crisis) + (\gamma_1 black_i + \gamma_2 college_i + \gamma_3 divorce_i + \gamma_4 physician_i) + \varepsilon_i \tag{7}$$

$$STD_i = \beta_0 + (\beta_1 * Gini_i) + (\beta_2 * crisis) + (\gamma_1 black_i + \gamma_2 college_i + \gamma_3 divorce_i + \gamma_4 physician_i) + \varepsilon_i \tag{8}$$

The full results of the OLS regression estimation of the effect of the economic crisis are reported in Table 9. The coefficient for the economic crisis indicator variable is statistically significant in influencing age-adjusted mortality and the diabetes prevalence rates. However, it is not statistically significant in influencing the infant mortality rate or the STD rate. These regression results demonstrate that during years of the economic crisis, we expect an approximately 693 additional deaths per 100,000 people per year. During non-economic crisis years, the expected number of deaths is actually higher, at 720 deaths per 100,000 people per year. While this seems counterintuitive, this fact has been well established in the literature.[21] Within the United States, nursing homes for the elderly are consistently understaffed when the economy is healthy. During this period, low-skilled workers quit their nursing home jobs, and transition into other industries where there are higher wages and better benefits. As a result, the elderly receive a lower quality of care and death rates increase in nursing homes during periods of economic expansion. These regression results also indicate that infant mortality, diabetes prevalence, and STD rates stay relatively the same, whether the economy is in the midst of a recession or not.

Table 9: Regression Results, Given the Economic Crisis

	(1) Mortality	(2) Infant	(3) Diabetes	(4) STDs
Gini	273.05***	3.47***	5.40***	11.20***
	(29.14)	(0.86)	(0.34)	(0.54)
Black	1.81***	0.069***	0.053***	0.148***
	(0.07)	(0.002)	(0.0009)	(0.001)
College	-4.82***	-0.035***	-0.094***	0.016***
	(0.10)	(0.003)	(0.001)	(0.002)
Divorce	10.03***	0.070***	0.62***	0.062***
	(0.40)	(0.012)	(0.004)	(0.007)
Crime	15.80***	-0.035		
	(1.71)	(0.049)		
Injury	0.013***	0.0002***		
	(0.0003)	(9.49e-06)		
Physicians	-8.26	0.68***	-2.50***	0.836***
	(5.29)	(0.16)	(0.06)	(0.10)
Crisis	-13.86***	3.09e-17	-0.91***	-1.74e-17
	(1.90)	(0.57)	(0.02)	(0.036)
_cons	707.01**	4.33***	10.29***	-4.72***
	(14.11)	(0.42)	(0.17)	(0.26)
N	14,687	14,880	15,690	15,690
R^2	47.99	16.06	57.27	53.77
RMSE	112.54	3.42	1.41	2.20

Note: Standard errors in parentheses
= "* p<0.10 ** p<0.05 *** p<0.01"

Income per Capita

We then perform a robustness check, incorporating income per capita at the state level. The full results of the OLS regression estimation of the effect of per capita income are reported in Table 10. The coefficient for income per capita at the state level is statistically significant on all four health indicators. It is statistically significant at the one percent level in influencing the age-adjusted mortality rate, the infant mortality rate and STD rates, and is statistically significant at the five percent level in influencing diabetes prevalence rates. These regression results indicate that for every thousand dollar increase in the income per capita at the state level, we expect approximately 3.5 less deaths per 100,000 people per year. In other words, we expect more affluent states to have slightly lower age-adjusted mortality rates. This makes intuitive sense, as richer states have citizens that can afford better healthcare, more nutritious food, perhaps have lower levels of stress, among many other factors that contribute to mortality.

For infant deaths, we expect that for every thousand dollar increase in the income per capita at the state level, we expect approximately 0.02 less infant deaths per 1000 births. This is a fairly negligible amount. The expected change in the diabetes rate is also fairly negligible given income per capita at the state level. For every thousand dollar increase in the income per capita at the state level, we expect approximately 0.07 less diabetes diagnoses per capita. And finally, for STD rates, we expect that for every thousand dollar increase in the income per capita at the state level, we expect approximately 0.3 less STD cases 1,000 people. This tells us that income per capita at the state level has a minimal influence on infant mortality, diabetes prevalence and STD rates, but does have a larger impact on the age-adjusted mortality rate.

Table 10: Regression Results, Given Income per Capita at the State Level

	(1) Mortality	(2) Infant	(3) Diabetes	(4) STDs
Gini	238.89***	3.27***	4.62***	10.87***
	(29.20)	(0.86)	(0.35)	(0.54)
Black	1.73***	0.068***	0.052***	0.148***
	(0.07)	(0.002)	(0.0009)	(0.001)
College	-4.46***	-0.033***	-0.086***	0.020***
	(0.10)	(0.003)	(0.001)	(0.002)
Divorce	9.59***	0.067***	0.052***	0.058***
	(0.40)	(0.011)	(0.005)	(0.007)
Crime	17.05***	-0.029		
	(1.70)	(0.050)		
Injury	0.012***	0.0002***		
	(0.0003)	(9.56e-06)		
Physicians	-1.54	0.72***	-0.116*	0.89***
	(5.26)	(0.16)	(0.0001)	(0.102)
Incomecapita	-3.54***	-0.021***	-0.07**	-0.3***
	(0.22)	(0.007)	(0.003)	(0.004)
_cons	835.69***	5.13***	13.53***	-3.58***
	(16.39)	(0.49)	(0.20)	(0.305)
N	14,687	14,880	15,690	15,690
R^2	48.69	16.12	54.84	53.92
RMSE	111.77	3.42	1.44	2.20

Note: Standard errors in parentheses
= "* p<0.10 ** p<0.05 *** p<0.01"

Population Density

We also perform a robustness check, using the same original regression equations, but additionally for population density at the state level. Population density may have a direct relationship with population health, for a number of different reasons. For one, high population density, can lead to a more rapid spread of disease and illnesses. Additionally, there are more traffic accidents and higher rates of violent crime in areas with high population density. However, high population density is also associated with higher quality healthcare facilities, such as specialists, level-one trauma centers, and large research hospitals. These facilities are almost exclusively located in large urban centers, not only to serve larger populations, but also due to the fact that they are often associated with large research universities. One would expect that living within close proximity to high-quality healthcare facilities would decrease mortality. However, despite this, we cannot say with certainty which one of these relationships dominates the other. It is for this reason that we see the sign of the coefficient fluctuating between negative and positive, yet always around zero, for the four health indicators.

The full results of the OLS regression estimation of the effects of population density are reported in Table 11. The coefficient for population density at the state level is statistically significant all four health indicators. It is statistically significant at the one percent level in influencing the age-adjusted mortality rate, diabetes prevalence, and STD rates, and at the five percent level in influencing the infant mortality rate. These regression results indicate that for every increase in the population density of 1,000 people per square mile, we expect approximately 0.00002 less deaths per 100,000 people per year. In other words, we expect states with a higher population density to have slightly lower age-adjusted mortality rates. The expected change in the infant mortality rate, given population density at the state level, is also fairly negligible. We see similar results for diabetes prevalence and STD cases per 1,000 people. This implies that while the relationship between population density and health indicator variables are statistically significant, the real-world impact is so small; it is virtually non-existent.

Table 11: Regression Results, Given Population Density at the State Level

	(1) Mortality	(2) Infant	(3) Diabetes	(4) STDs
Gini	273.40***	3.47***	5.40***	11.2***
	(29.18)	(0.86)	(0.36)	(0.54)
Black	1.83***	0.069***	0.053***	0.150***
	(0.07)	(0.002)	(0.0009)	(0.001)
College	-4.82***	-0.035***	-0.094***	0.017***
	(0.10)	(0.003)	(0.001)	(0.002)
Divorce	10.03***	0.069***	0.62***	0.06***
	(0.40)	(0.012)	(0.005)	(0.007)
Crime	15.92***	-0.033		
	(1.71)	(0.049)		
Injury	0.013***	0.0002***		
	(0.0003)	(9.50e-06)		
Physicians	-5.75	7.24***	-2.17***	1.0***
	(5.34)	(0.16)	(0.07)	(0.102)
Popdensity	-0.00002***	-2.85e-07**	-2.3e-07***	-1.1e-06***
	(4.80e-06)	(1.45e-07)	(6.18e-08)	(9.20e-08)
_cons	701.0 ***	4.37***	10.87***	-0.46***
	(14.10)	(0.42)	(0.17)	(0.26)
N	14,687	14,880	15,690	15,690
R^2	47.84	16.08	53.00	54.20
RMSE	112.69	3.42	1.47	2.19

Note: Standard errors in parentheses
= "* p<0.10 ** p<0.05 *** p<0.01"

Unemployment Rate

We also perform a robustness check, using the same original regression equations, but additionally for the unemployment rate at the county level. It is important to check the relationship between the unemployment rate and health indicator variables, since in the United States, these two items are invariably linked. According to the United States Census Bureau, as of 2010, roughly half of all Americans obtain health insurance through an employer. In this same year, ten percent of Americans purchased health insurance directly, approximately one-third of Americans were enrolled in a public health insurance program, and another ten percent went uninsured[5]. It has been well-documented in the literature that within the United States, people who lack health insurance are more likely to die and have worse health outcomes than those with health insurance[26]. Since there is a clear relationship between employment and health insurance exists, this robustness check can provide us with information that the relationship between the Gini coefficient and health indicators cannot.

The full results of the OLS regression estimation are reported in Table 12. The coefficient for the unemployment rate is statistically significant all four health indicators. These regression results indicate that for every unit increase in the unemployment rate, we expect approximately 3.3 less deaths per 100,000 people per year. In other words, we expect states with a higher unemployment rates to have slightly lower age-adjusted mortality rates. While this seems to conflict with what the literature has established about employment and health, we also need to account for the fact that unemployment increases during periods of recession. As we saw earlier, mortality actually decreased during the economic recession of 2007 to 2009. Therefore, I believe the negative relationship between the unemployment rate and mortality takes into account the effects of the economic crisis on age-adjusted mortality. Since these two relationships have opposing effects, I believe the regression results demonstrate that the impact of the economic crisis on mortality is stronger than the effect of the unemployment rate on mortality.

For infant deaths, we expect that for every increase in the unemployment rate, there will be approximately 0.03 less infant deaths per 1000 births. This is a fairly negligible amount. The expected change in the diabetes rate is also fairly negligible. For every increase in the unemployment rate, we expect approximately 0.13 less diabetes diagnoses per capita. And finally, for STD rates, we expect that for every increase in the unemployment rate, approximately 0.07 more STD cases per 1,000 people. Again, this is a fairly negligible amount.

Table 12: Regression Results, Given The Unemployment Rate

	(1) Mortality	(2) Infant	(3) Diabetes	(4) STDs
Gini	280.09***	3.52***	4.95***	10.95***
	(1.89)	(0.86)	(0.35)	(0.54)
Black	1.89***	0.069***	0.049***	0.146***
	(0.07)	(0.002)	(0.0009)	(0.001)
College	-4.99***	-0.037***	-0.086***	0.021***
	(0.10)	(0.003)	(0.001)	(0.002)
Divorce	10.50***	0.073***	0.04***	0.048***
	(0.40)	(0.012)	(0.005)	(0.007)
Crime	16.82***	-0.027		
	(1.71)	(0.049)		
Injury	0.013***	0.0001***		
	(0.0003)	(9.55e-06)		
Physicians	-9.09*	0.68***	-2.37***	0.843***
	(5.27)	(0.16)	(0.07)	(0.101)
Unemployment	-3.29***	-0.03***	0.129***	0.073***
	(0.516)	(0.009)	(0.004)	(0.006)
_cons	716.3***	4.47***	10.15***	-5.12***
	(14.14)	(0.42)	(0.17)	(0.26)
N	14,687	14,880	15,690	15,690
R^2	48.18	16.11	56.12	54.21
RMSE	112.33	3.42	1.42	2.19

Note: Standard errors in parentheses
= "* p<0.10 ** p<0.05 *** p<0.01"

CHAPTER IV

DISCUSSION

In this study, we demonstrate that the health of American citizens is negatively affected by increasing disparities in income, even when controlling for confounding factors. Income inequality is a valuable predictor of the age-adjusted mortality, infant mortality, diabetes prevalence, and rates of STDs. Counties with higher levels of income inequality experience higher mortality rates, diabetes diagnoses and rates of STDs than do counties with lower income inequality. This study extends previous research on the topic to the United States county level, and finds that these results apply across the country.

Our results also indicate that characteristics inherent to the individual states play a role in income inequality's effect on health indicators. The impact of income inequality on health indicators becomes more limited, and is roughly halved, by controlling for state fixed effects.

We also demonstrate that the economic crisis had a noticeable effect on the relationship between income inequality and age-adjusted mortality. Expected age-adjusted mortality decreases during the years of the economic recession, due in large part to an influx of low-skill workers transitioning into jobs caring for the elderly in nursing homes. Infant mortality rates, diabetes prevalence, and STD rates stay relatively the same, even if the health of the economy changes.

The relationship between income inequality and the four health indicators still holds even when accounting for income per capita at the state level. However, we expect that when controlling for income inequality at the county level, counties located in more affluent states will have lower age-adjusted mortality rates, fewer infant deaths, fewer diabetes diagnoses, and lower rates of STDs.

Population density at the state level has a significant but minimal effect on the relationship between income inequality and the four health indicators. We expect that states with higher population densities have slightly lower mortality rates, infant mortality rates, and diabetes rates, and slightly higher STD rates.

Finally, we demonstrate that the unemployment rate has a significant effect on age-adjusted mortality, and a negligible effect on infant mortality rates, diabetes prevalence, and STD rates. We would expect counties with higher unemployment rates have slightly lower age-adjusted mortality rates. This may be due in part to an increase of low-skill workers transitioning into nursing homes jobs during periods of economic recession. Infant mortality rates, diabetes prevalence, and STD rates stay relatively the same, even changes in the unemployment rate.

These findings highlight the significance of income inequality in our society, and provide an insight into the characteristics we can expect from a more unequal society. In the years since 2010, income inequality has continued to increase within the United States. As we have seen, an increase in income inequality directly correlates with higher mortality rates, additional diagnoses of diabetes, and higher rates of STDs. The hope is that readers and policymakers alike will use these conclusions to identify targets for policy intervention; policies which will hopefully turn the tide on this growing problem. We can no longer pretend that income inequality is an abstract term without real-world consequences. The impacts are clear, and they are adversely affecting the health and lives of the most vulnerable American citizens.

REFERENCES

1. Allegretto, S. (2011). The State of Working America 2011: Through Volatility and Turmoil, The Gap Widens. *Economic Policy Institute*, (Issue Brief No. 292).

2. Alvaredo, F., Atkinson, A., Piketty, T., & Saez, E. (2013). The Top 1 Percent in International and Historical Perspective. *Journal of Economic Perspectives*, *Vol. 27*(3), Pages 3-20.

3. Atkinson, A., Piketty, T., & Saez, E. (2011). Top Incomes in the Long Run of History. *Journal of Economic Literature*, *49*(1), 3–71-3–71.

4. Deaton, A. (2003). Health, Inequality, and Economic Development. Jou*rnal of Economic Literature*, XLI, 113-158.

5. DeNavas-Walt, C., Proctor, B., & Smith, J. (2011). Income, Poverty, and Health Insurance Coverage in the United States: 2010. *U.S. Census Bureau*, Current Populations Reports: Consumer Income.

6. Fajnzylber, P., Lederman, D., & Loayza, N. (2000). Crime and Victimization: An Economic Perspective. *Economía 1*, no. 1, 219-302.

7. Harling, G., Subramanian, S., Bärnighausen, T., & Kawachi, I. (2013). Income inequality and sexually transmitted in the United States: Who bears the burden? *Soc Sci Med*, *Feb 2014*(102), 174-82.

8. Judge, K., Mulligan, J., & Benzeval, M. (1998). Reply to Richard Wilkinson. *Soc. Sci. Med, 47*, 983–85.

9. Kaplan, G., Pamuk, E., Lynch, J., Cohen, R., & Balfour, J. (1996). Inequality in Income and Mortality in the United States: Analysis of Mortality and Potential Pathways. *Brit. Med .*, *312*, 999–1003.

10. Kawachi, I., Kennedy, B., & Prothrow-Stith, D. (1997). Social Capital, Income Inequality, and Mortality. *American Journal of Public Health*, *87*, 1491–98.

11. Kennedy, B., Kawachi, I., & Prothrow-Stith, D. (1996). Income distribution and mortality: Cross sectional ecological study of the Robin Hood index in the United States. *BMJ*, 312, 1004-1007.

12. Kennedy, B., Kawachi, I., & Prothrow-Stith, D. (1996). Important Correction. *BMJ*, 312.

13. LaClere, F., & Soobader, M. (2000). The effect of income inequality on the health of selected US demographic groups. *American Journal of Public Health*, 90, 1892-1897.

14. Lynch, J., Kaplan, G., Pamuk, E., Cohen, R., Heck, K., Balfour, J., & Yen, I. (1998). Income Inequality and Mortality in Metropolitan Areas of the United States. *American Journal of Public Health*, 88, 1074–80.

15. Lynch, J., Davey-Smith, G., Hillemeier, M., Shaw, M., Raghunathan, T., & Kaplan, G. (2001). Income Inequality, Psychosocial Environment and Health: Comparisons across Wealthy Nations. *Lancet*, 358, 194–200.

16. McLaughlin, D., & Stokes, C. (2002). Income Inequality and Mortality in US Counties: Does Minority Racial Concentration Matter? *American Journal of Public Health*, 92, 99-104.

17. Mellor, J., & Milyo, J. (2001). Reexamining the Evidence of an Ecological Association between Income Inequality and Health. *J. Health, Politics, Policy, Law,* 26, 487–522.

18. Mujica, O., Castillo-Salgado, C., Bacallao, J., Loyola-Elizondo, E., Christina Schneider, M., Vidaurre, M., & Alleyne, G. (2000). Income Inequality and Suicide Risk in the Americas. *Pan-American Health Org*.

19. Murthi, M., Guio, A., & Drèze, J. (1995). Mortality, Fertility, and Gender Bias in India: A District Level Analysis. *Population Devel*. Rev. 21, 745–82.

20. Pickett, K., Kelly, S., Brunner, E., Lobstein, T. & Wilkinson, R. (2005). Wider income gaps, wider waistbands? *Epidemiological Community Health*, 59, 670–674.

21. Piketty, T. (2001). Income Inequality in France, 1901-1998. *Journal of Political Economy*, 111, 1004-1042.

22. Piketty, T., & Saez, E. (2003). Income Inequality in the United States, 1913-1998. *Quarterly Journal of Economics*. 118, 1-39. (Tables and Figures Updated to 2013 in Excel format, January 2015).

23. Stevens, H., Miller, D., Page, M., & Filipski, M. (2011). The Best of Times, the Worst of Times: Understanding Pro-cyclical Mortality. *National Bureau of Economic Research, Inc., NBER Working Papers*, 17657.

24. Jones Jr., A., & Weinberg, D. (2000). The Changing Shape of the Nation's Income Distribution: 1947 - 1998. *U.S. Census Bureau*, P60-204.

25. Wilkinson, R. (1996). Unhealthy Societies: The Affliction of Inequality. London: Routledge.

26. Wilper, A., Woolhandler, S., Lasser, K., Mccormick, D., Bor, D., & Himmelstein, D. (2009). Health Insurance and Mortality in US Adults. *American Journal of Public Health*, 99(12), 2289-2295.