State Level Income Inequality and Individual Self-Reported Health Status: Evidence from the United States

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Abstract

The relative income hypothesis theorizes an individual's income, relative to the income of their peers, adversely affects their health. There is empirical evidence to support the relative income hypothesis, showing a negative statistical relationship between income inequality and health. The literature is unsettled on the relevant level of geography to measure income inequality, as well as other control variables in the estimation. This paper contributes to this literature by asking how state level income inequality affects the probability of an individual having excellent self-reported health. The relative income hypothesis is tested using individual level data from the Current Population Survey in the United States, and is supplemented with state level income inequality and healthcare spending data from 1996-2009. A logit model with clustered standard errors is employed, with marginal effects reported. Results suggest no statistically significant effects within the full sample. However, if the analysis is restricted to the five most or least equal states, there is a statistically significant relationship between income inequality and health. The most equal states exhibit a positive (but small) relationship between inequality and health, while the least equal exhibit a negative (but small) relationship. While a statistically significant association is found for these samples, the point estimates are not economically significant. The results are robust to the specific income inequality measure, lag structure of income inequality, and time period of analysis. The results do not support the relative income hypothesis. The implication is the effect of income inequality on health may be overstated

Key Words

Gini Coefficient; Health Inequality; Income Inequality; Self-Reported Health

1. Introduction

Despite economic prosperity, the United States has always lagged behind many developed countries in health indicators. The United States is now ranked below the average of the Organization of Economic Cooperation and Development[1] (OECD) in terms of life expectancy, and was ranked number one in percent of adult population that is obese in 2012, even though the U.S. healthcare expenditure is significantly larger than any other OECD country (OECD Health Statistics, 2015). The United States' healthcare expenditure is known for being extremely unequal (Ruger, 2006). The disparities in healthcare quality available to different citizens based on geography and income allow for different classes of care to exist. This, at least, partially explains the lagging health indicators when so much money is being put into the system – only some citizens benefit from the expenditure.

While the U.S. economy has continued to grow significantly, this growth has not been equally distributed across the population. As of 2013, the United States' income inequality (as measured by the Gini coefficient) was fourth when ranked across all OECD countries. As well, income inequality has risen much faster than any other OECD country, apart from Mexico, for the past 10 years (OECD Income Distribution Database, 2014).

Healthcare inequality and income inequality correlate with one another. As income inequality rises, those at the high end of the distribution are able to pay for high quality healthcare either "out of pocket" or through private insurance. This creates a self-perpetuating cycle. The very rich are able to afford better health care, and as such, are able to go back to work faster and earn more money. The Affordable Care Act, enacted in 2010, was

[1] An organization which brings together 34 countries on talks of economic progress and world trade

created to help alleviate this inequality by allowing for the low end of the distribution to be able to purchase subsidized health insurance.

While some of these two trends are related to the fact that the United States' healthcare system is relatively unequal, a hypothesis presented by Richard Wilkinson (1996) posits income inequality and health trends are related. Specifically, income inequality harms the health of citizens. The relative income hypothesis explains that humans, after expenses for necessities are accounted for, do not care as much about the actual level of income they have. Instead, they make comparisons of income between themselves and peers to determine their wealth. This comparison is what impacts individuals' health in a society.

If the relative income hypothesis holds true, it has large implications for policy within the United States. Income inequality has become a very controversial topic in American political discourse since the financial crisis of 2008. The relative income hypothesis may help shape this debate. Advocating for policies which shrinks the income distribution may help the overall health of the nation. As the United States is struggling with healthcare solutions, the relative income hypothesis can help benefit overall health. While disentangling income effects from income inequality effects on health is difficult, investigating the effect of income inequality on citizen health is important and can help the United States population strengthen their health.

This paper will investigate the relative income hypothesis, using state-level income inequality and individual level health data. This data will be tested using a logit model. I hypothesize that I will find a strong statistical relationship between income inequality and health.

2. Literature Review

The large literature looking at income and health can be sorted into two distinct branches. The first branch investigates the absolute income hypothesis, which focuses on the relationship between an individual's absolute level of income and their health. The second branch investigates the relative income hypothesis, which focuses on the relationship between an individual's level of income relative to others in society and the individual's level of health. The focus of the literature review is on the relative income hypothesis. This is because while research regarding the absolute income hypothesis has reached a reasonable consensus on the relationship, the same cannot be said for the relative income hypothesis.

The measurement of income inequality and health, understanding the mechanisms between income inequality and health, as well as the econometric methods to test the relative income hypothesis are discussed below.

2.1 Mechanisms Relating Income Inequality to Health

An important part of the relative income hypothesis literature is attempting to disseminate the mechanisms in which income inequality can affect health. The literature focuses on three specific mechanisms.

First, areas with higher income inequality spend less of their budget on public education and overall show poorer education outcomes (Kaplan, 1996). This correlation exists, at least partially, due to diverging interests between the poor and rich (Krugman, 1996). The very rich do not need the government to spend money on public education, and have more political clout as inequality rises. As the level of funding in public school decreases, the quality of education provided decreases. As such, children who go through the public school system have a worse chance of being able to pursue post-secondary education compared to those in private schools. This educational difference drives income inequality.

Second, larger income inequality depreciates social capital within a community. Social capital, as defined as social institutions, trust between citizens, and civic associations benefit all citizens but especially those at the low end of the income distribution (Coleman, 1990; Putnam, 1993). The depreciation of social capital occurs due to the similarities between citizens becoming smaller as the income distribution becomes wider.

Finally, the most important and discussed mechanism which transmits income inequality into decreasing health is individual psychosomatic stress. Relatively low income leads to a host of different psychological maladies such as depression and stress (Dressler, 1996, 1998). Individuals compare themselves with neighbours and peers and attempt to "keep up with the Joneses", leading them to work more than they should and worry when they do not. Regardless of an individual's income, they compare themselves to individuals richer than them, which leads to overwork and stress (Schor, 1998). The evidence of increased stress in manual, clerical, or other low wage employment has slowly increased over the past thirty years. The Whitehall study in the United Kingdom surveyed members of the British civil service and found individuals in lower levels of employment within the same industry were much more at risk of cardiovascular disease, smoking, and obesity (Fuller et al, 1980). These increased risk factors impacted these individuals far into their old age (Breeze et al, 2001). Individuals at the low end of the income distribution feel devalued or inferior when they compare themselves to individuals with higher income (Charlesworth et al, 2004). This is especially prevalent in American, where the ideology that hard work will always end in success is widespread. The "American Dream" leads unsuccessful people to believe it is entirely their fault that they are unsuccessful (Corak, 2013). This causes their stress to increase significantly and impact health.

2.2 U.S. Empirical Evidence of the Relative Income Hypothesis

National studies of the United States have demonstrated similar results overall. Using national United States data, roughly 83% of research previous to 2006 found strong support of the relative income hypothesis on health (Wilkinson and Pickett, 2006). Almost all of the papers in this study used multinomial or multilevel logistic regressions as well as several different estimations (different race, ethnic, or age subgroups or different inequality measures), meaning there are overwhelming results the relative income hypothesis does exist. However, when researchers begin to investigate using subgroups of the United States; the level of supportive research begins to dwindle from 83% of papers beings wholly supportive to 45% wholly supportive when using county, tracts, or parish data. However, as mentioned by Wilkinson and Pickett (2006), papers investigating very small areas are fundamentally researching a different topic than inequality on health. Instead, they are testing social comparisons within that small area. In these smaller areas, individuals compare themselves to their near equals instead of those much higher or much lower than them on an income distribution, called the "relative deprivation theory" in the literature (Runciman, 1966; Marmot, 2006; Wilkinson and Pickett, 2007). The smaller the area gets, the more a researcher is investigating income differences between the small groups, as opposed to income inequality as a whole. These differences between people within a community may not match up with state or national inequality trends. This is the main reason why studies investigating metropolitan areas in this literature find results which are weak and insignificant (Messener and Tardiff, 1986; Gold et al, 2001; Galea et al, 2003). However, some papers still do find a strong negative relationship between income inequality and health (Ettner, 1996; Kennedy, 1998; Ross, 2000)

2.4 Important Covariates

What covariates to include in the estimation of inequality and health has become a contentious issue in the literature. This is due to the issue of understanding exactly what mechanisms inequality harms health. Some mechanisms may flow through traditional control variables like race, which will give us a biased estimation (Subramanian and Kawachi, 2004). This is because the true effect of income inequality would not be fully captured by the inequality coefficient. Instead, some of the effect would move into the race coefficient. Usually, estimations include controls for education and individual income (Muller, 2002). However, even individual income has more recently become less often used. This is because researchers believe the mechanisms in the relationship between inequality and health are motivated by social difference – not absolute material purchasing power (Marmot, 2004). Including an individual's income would bias the estimate for the relative income hypothesis. It is argued including individual income with income inequality is "double counting" class differences and the inequality coefficient will be incorrect. When testing both the absolute and relative income hypothesis simultaneously, the absolute income effect is stronger when using a multinomial logistic estimation (Fiscella and Franks, 2000). Even if concerns over using individual income is ignored, the coefficient result in regards to inequality are usually similar if individual income is omitted or not (Subramanian and Kawachi, 2004). An important control variable which has gained universal acceptance is individual's age. Several different studies have demonstrated the age of an individual changes the relationship between income inequality and health (Smith 1998, 1999).

An important control variable which has started to gain prominence in the literature is social spending by the relevant government agency. This helps disentangle the mechanisms of the relationship between inequality and health. More equal societies, on average, have stronger social health programs. This may be the contributing factor to health, as opposed to inequality affecting individual's health (Judge, 1995). When social spending is controlled for, the relative income hypothesis findings become insignificant (Rostila, 2012). As this control variable is only coming into prominence, more study of its effect is required. Without social spending data available, researchers regularly use some kind of fixed effect to control for differences in spending. The issue with using state-level fixed effects is that income inequality is not particularly volatile, and the ranking of state's inequality is fairly constant over time. Thus, using a state fixed effect would be inappropriate (Goldstein et al, 2002). Instead, using a regional fixed effect will control for partial state differences, without the ranking being static (Mellor and Milyo, 2003; Gerdtham and Johannesson, 2004).

An important issue to consider is the problem of reverse causality. What most papers see is a relationship in which income inequality causes poor health, but some papers see at least some casualty moving in the opposite direction. Healthier individuals have the ability to work longer hours and earn more in wages. This drives income inequality (Smith, 1999). There has been less research done on this "reverse causality" as opposed to inequality driving health. In general, this reverse causality weakens coefficient results, and may explain why some studies result in weak or insignificant findings (Welch et al, 2001; Deaton, 2002; Bloom et al, 2004).

2.5 Summary

The literature suggests looking at the relative income hypothesis at the state level is most appropriate. Inequality within a state should affect an individual more than national inequality as it is closer to them. As well, it allows me to look at cross state variation, without the subsections becoming too small to measure with regards to overall income inequality. However, the literature in regards to self-reported health and income inequality at the state level is relatively sparse. This paper looks to add to the literature of state level income inequality and its effect on health. Through my review of the literature, I have found time fixed effects help eliminate confounding factors. As well, controlling for age is necessary as the relationship between inequality and health changes with age. Most control variables which have been used in this literature do not have a consensus on inclusion in estimation.

3. Empirical Methodology

Following the literature's empirical framework, I will be estimating a logistic (logit) regression (Lopez, 2004; Subramanian and Kawachi, 2004).

3.1 Logistic Model

The logit model uses a binary dependant variable and either continuous or binary explanatory variables. The empirical framework is as follows:

$$y_i = \Phi\left(\alpha + \beta_1 inequality_{sL} + \beta_2 (inequality)^2_{sL} + \beta_5 healthspend_s + \beta_4 X_i + \theta_t + \varepsilon\right) \quad (4)$$

where y_{it} is a binary variable equal to one if respondent i reports excellent or very good health, $inequality_{sL}$ is the inequality measure for state s with a lag of L, $healthspend_s$ is the social spending in state s per capita, and X_i are the other control variables for individual i (ethnicity, age, marital status, education, and sex). The control variables (X_i) are normally used as baseline controls (Subramanian et al, 2003). I use lagged inequality as the literature believes inequality takes two to four years to impact health, so I will test this by using lagged terms of two years, three years, and four years (Kennedy et al, 1998; Kahn et al, 2000). A squared inequality term is also included to attempt to capture a potential nonlinear relationship as some of the potential literature demonstrates the relative income hypothesis may be nonlinear (Lynch et al, 2004). γ are year fixed effects to control for any additional unobserved variables that affect health. A state fixed effect is not used due to the limited variation in state level inequality.

3.2 Marginal Effects

In the context of this literature, using the odds ratio is still not enough to get a good sense of the magnitude of the relationship between income inequality and health. The literature investigating the relative income hypothesis demonstrates the relationship may not be linear. The odds ratio, however, assumes a relationship to be linear. Regardless of where on the distribution the data point is, the marginal effect is the same. Instead of using the odds ratio, I will use the marginal effects at different points in the inequality distribution (Mellor and Milyo, 2003). The marginal effects are calculated by deriving the empirical model at a particular point of inequality. This instantaneous change at a certain level of inequality is an approximate measure of a one unit change in the explanatory variable (Cameron and Trivedi, 2010). Taking the marginal effect at different points of the income inequality distribution, as well as plotting the marginal effects across the entire distribution allows me to see the relationship without assuming the effect is linear and homogenous.

The marginal effects are taken as a derivative of the logit model. In this case, all explanatory variables which are not measuring inequality are set to their means. The inequality measure is set to the first or third quartile or the mean. Mathematically, the marginal effect takes the form:

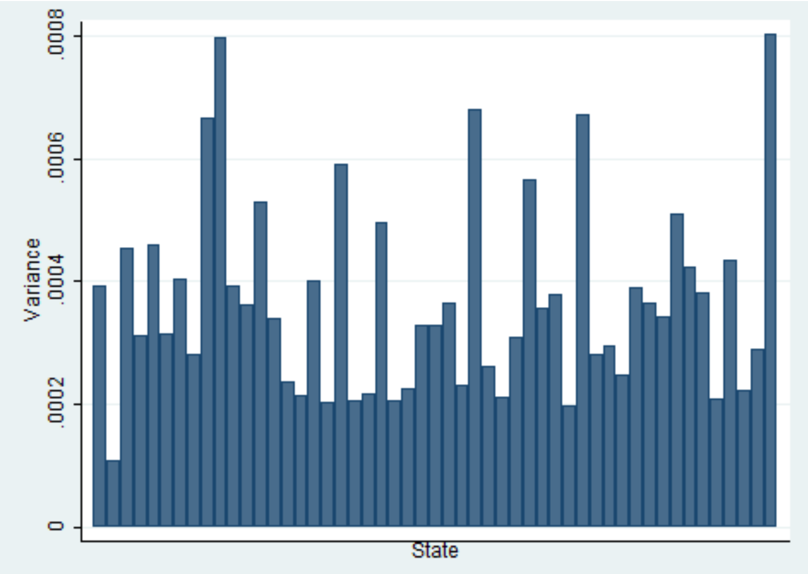
$$\frac{dy_i}{d(inequality)} = F'(y) \qquad (5)$$

The solution to equation 1 gives us the marginal effect at a particular point of the inequality distribution.

3.3 State Fixed Effects

Table 1 demonstrates the states' inequality measures move in the same direction and are strongly correlated. Figure 1 shows the variance across the sample period by state using the top decile measure. Each state's inequality varies only a small amount over the time period. As such, using state level dummies would over identify state trends between the inequality measure and the dummy variables.

Figure 1 – State-level Variance using the Top Decile, from 1996-2009



The literature is split on whether a binomial or multinomial model is more appropriate (Fiscella and Franks, 2000; Weich et al; 2002; Mcleod et al, 2003; Xi et al, 2005). I have chosen to use a binary health indicator. While I lose the nuance of which exact category individuals are moving into, I'm still able to ask the research question "does income inequality affect an individual's self-reported health" in a much easier to interpret way.

3.4 Clustered Standard Errors

Of concern in much of the literature is the estimation of standard errors. Much of the literature on empirically testing the relative income hypothesis uses multi-level models to account for data hierarchy and correlated errors. An alternative to multi-level modelling is to use clustered standard errors. I am using clustered errors to account for different levels of variance in the data, and to eliminate correlation in the error. Individuals living within the same state are more likely to share unobserved characteristics. Without clustering, the standard errors in the estimation will violate the assumption the errors are independent. As such, the “sample size” of the data is incorrect – each data point may not add the same amount of explanatory power. The first individual measured in a state may produce a lot of explanatory power, while the second may only add some explanatory power in addition, and so on. In the data used in this paper, the “intraclass correlation” (i.e. the correlation between individuals living in the same state) is 0.83 using the Gini measure. This demonstrates the states’ inequality measures move in the same direction and are strongly correlated. Clustering by state adjusts the sample size to more accurately fit the explanatory power of the data and help eliminate this correlation (Cameron, Gelbach, and Miller, 2008).

3.5 Hypothesis

I expect the top decile measure’s marginal effects to be negative. For these state level measures, a negative sign on the income inequality coefficient demonstrates as income inequality rises, the probability of an average citizen being in the good health group decreases. This would validate the relative income hypothesis.

4. Data

The paper combines data from three different sources: (i) American Current Population Survey; (ii) Centres for Medicare and Medicaid Services; and (iii) Mark Frank (2009).

4.1 American Current Population Survey

All individual level data comes from the American Current Population Survey (CPS). The survey is jointly sponsored and collected by the Census Bureau and the Bureau of Labour Statistics and collects data on wages, hours worked, health, as well as basic demographic information (such as age, sex, years of education, and marital status). Approximately 60,000 households are part of the CPS each year, and then followed for two consecutive years. The CPS files were obtained through the Integrated Public Use Microdata Series (IPUMS) at the University of Minnesota. The IPUMS harmonizes the CPS data from 1962 to 2014. Since the rest of my data is from 1996-2009, I will be using the CPS from each year in the sample range.

4.1.1 Variable Descriptions

Self-reported health is a categorical variable, in which an individual selects the category they feel their health belongs to. The five categories are poor, fair, good, very good, and excellent. In the estimation, self-reported health is transformed into a binary choice between very good or excellent health chosen equalling one, and all other health choices equalling zero (excellent/verygood). This choice is made due to the asymmetry of people choosing their health. A majority of people place themselves in the “excellent” or “very good” category of self-reported health. Choosing the “good” category of self-reported health to be a part of the bad outcome group is primarily to not have an extreme majority of individuals in the good outcome group. Roughly 70% of the sample has selected into the excellent or very good category. If the good category was included, roughly 85% of the sample would be in the excellent health category. Age is measured as a number of whole years. Sex is a dummy variable in which female is equal to 1, and male is equal to 0. Marital status is a dummy variable in which married individuals equal 1, and non-married (single, divorced, or widowed) is equal to 0. Years of education is initially given as a codebook of different values. I have recoded the education to data to create dummy variables to indicate the level of education an individual has achieved. The categories are: some high school, high school graduate, some college, bachelor’s degree graduate.

4.2 Centers for Medicare and Medicaid Services Data

Data on state level healthcare spending per capita (healthspend) comes from the Centers for Medicare and Medicaid Services (CMMS). The CMMS measure of healthcare spending includes all hospital care, physician services, and retail prescription drugs. Medicare and Medicaid fund almost all of these services. Medicare's target population are Americans over 65 who have paid into the system over the lifetime as well as younger citizens with severe disabilities. Medicaid is a program which targets citizens and families who are designated as "low income". The definition of "low income" is left open to interpretation by each state separately. While Medicare is a federal program applied across all states in the exact same way, Medicaid is run differently in every state. The data does not disseminate how much of the total healthcare spending per capita is applied from Medicare or Medicaid, so each state starts with a base amount of total healthcare expenditure per year. However, since each state has different rules for how Medicaid is used, the amount varies across all states. The Centers for Medicare and Medicaid Services have not published this data for the most recent years. As such, the dataset used in this paper is truncated from 1996-2012 to 1996-2009.

4.3 Inequality Data

Income inequality data comes from a data set from Mark Frank (2009). The data is at the state level from 1996-2012. The measure used throughout this paper is the top decile measure. This measure is calculated based on United States IRS data.

4.3.1 Gini Coefficient

The Gini coefficient is constructed by measuring the distance between a Lorenz curve and a 45° line. The distance between the Lorenz curve and a 45° line is the inequality within a state. The 45° line represents equality. As the graph moves across the income distribution, the 45° line demonstrates an equal rise in the cumulative frequency of the income distribution. A Gini coefficient of 0 represents perfect equality. There is no deviation from the 45° line. A

Gini coefficient of 1, however, represents perfect inequality. The plotted line cannot deviate more from the 45° line. Figure 2 shows the Lorenz curve for the data used in this paper.

Figure 2 – Lorenz Curve

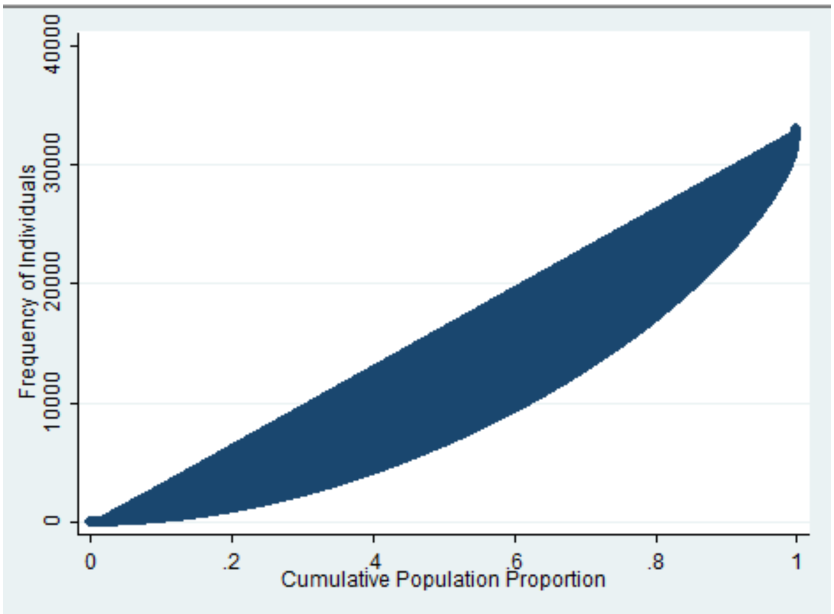
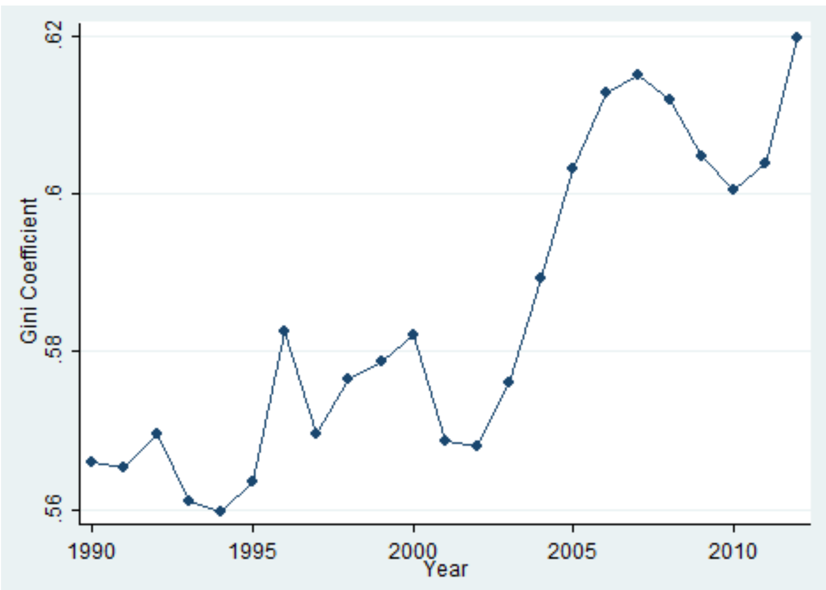


Figure 3 shows the average Gini coefficient (averaged across states) from 1996 to 2012. Figure 3 suggests a nonlinear increase in the level of inequality over the time period selected.

Figure 3 – Average Annual Gini Coefficient (across states), from 1996 to 2012



4.4 Sample Restrictions

After removal of missing value data points and children from the data set, I have 973,054 observations across the fifty states (plus the District of Columbia) for the years 1996-2009. The data is relatively spread equally between all time periods and states.

4.5 Descriptive Statistics

Table 2 presents descriptive statistics (mean, min, and max) for the analysis sample. We can see the sample is nearly equivalent across sexes (49% are female), 11% of the sample is black, 58% of the sample is married, and the sample is relatively well educated. 35% of the population has a high school diploma and 22% have a bachelor's degree.

Table 2 – Summary Statistics

Variable	Mean	Min	Max
Individual Level - Proportion of population that:			
is in very good or excellent health	69%	0%	100%
is female	49%	0%	100%
is black	11%	0%	100%
did not finish highschool	8%	0%	100%
have a highschool diploma	35%	0%	100%
have some college education	34%	0%	100%
have a bachelor's degree	22%	0%	100%
is married	58%	0%	100%
Inequality			
Top Decile Share	0.45	0.36	0.57

The inequality indicator seems higher than what is usually published nationally by the United States government. There are a few reasons why this is. The data is created using IRS tax data. The assumption is the individuals at the lowest end of the distribution are less likely to file taxes and as such, the measure may be biased upwards from their true value. As well, the coefficient is averaged across all states without weighting. As such, very concentrated states with small populations are treated exactly the same as less concentrated, more populated states. This would explain why state level inequality measures are higher than the officially published national inequality measures.

Table 3 presents individual level summary descriptions of the five most equal (least inequality) and five least equal (most inequality) states. These states are ranked based on the top decile share coefficient averaged across the full time period. The five most equal states are West Virginia, Iowa, Maine, Indiana, and North Dakota. The five least equal states are New York, Connecticut, District of Columbia, Florida, and Nevada. This table demonstrates there is some variation between states of different inequality at the average individual level. The more unequal states have a slightly higher average proportion of individuals in very good or excellent health, a much more black population, and a larger discrepancy between individuals at the low and high ends of the education spectrum.

Table 3 – Summary Statistics for the Most and Least Equal States

5 Most Equal States	Mean	Min	Max
Individual Level - Proportion of population that:			
is in very good or excellent health	69%	0%	100%
is female	50%	0%	100%
is black	3%	0%	100%
did not finish highschool	7%	0%	100%
have a highschool diploma	39%	0%	100%
have some college education	34%	0%	100%
have a bachelor's degree	19%	0%	100%
is married	63%	0%	100%
5 Least Equal States			
Individual Level - 5 Least Equal States			
is in very good or excellent health	70%	0%	100%
is female	49%	0%	100%
is black	17%	0%	100%
did not finish highschool	9%	0%	100%
have a highschool diploma	36%	0%	100%
have some college education	32%	0%	100%

have a bachelor's degree	23%	0%	100%
is married	55%	0%	100%

4.5.2 Health Status

From 1996-2009, the proportion of individuals which choose their health to be in the very good or excellent category is fairly static, as seen in Figure 4. However, from figure 5, we can see when averaged across the sample time period, there is variation between states. This means the hypothesized relationship is less due to a trend across all states, but is more likely due to variation across the states.

Figure 4 – Proportion of State's Population in Very Good or Excellent Health (across states), 1996-2012

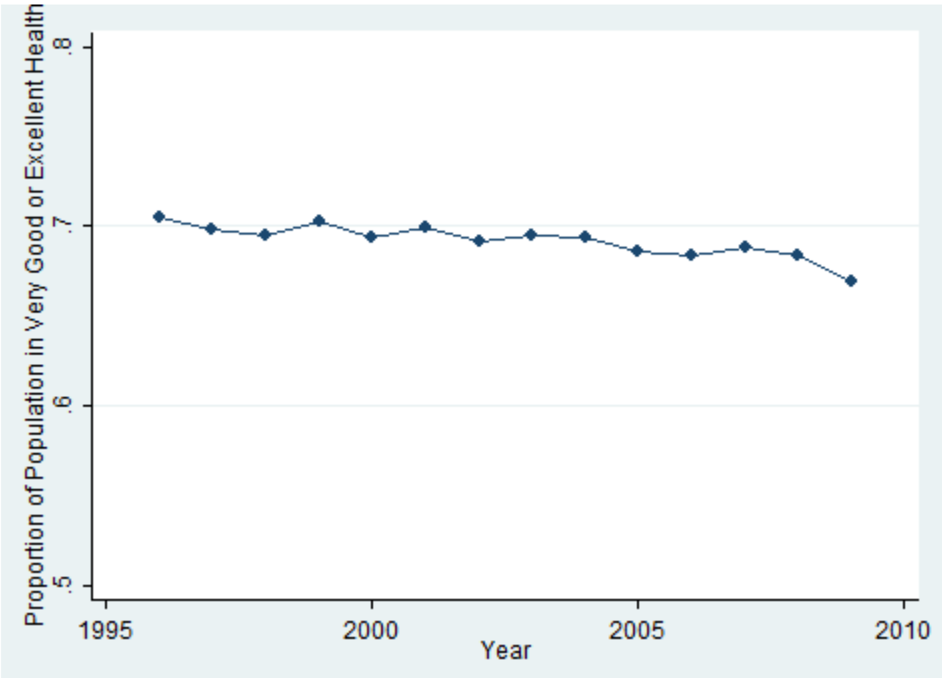
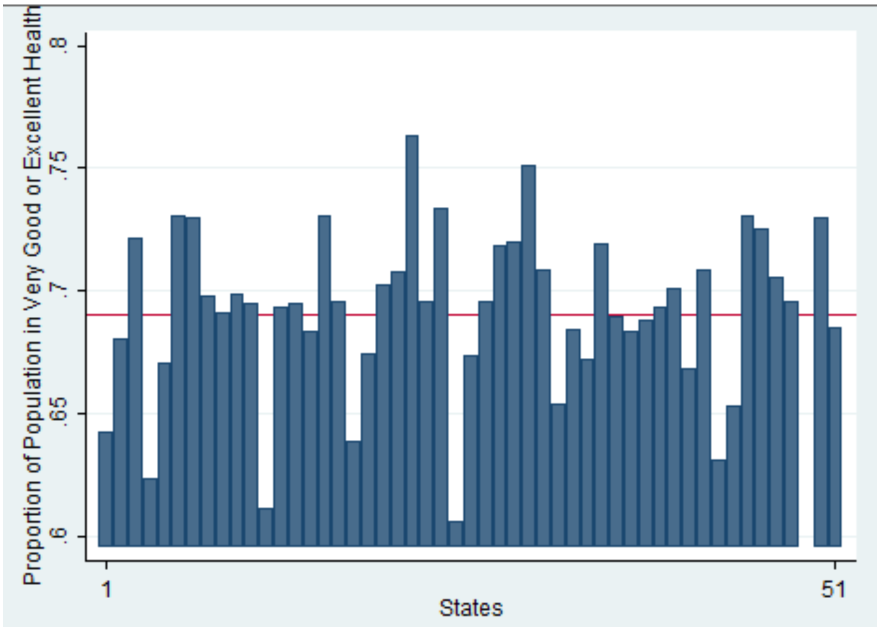


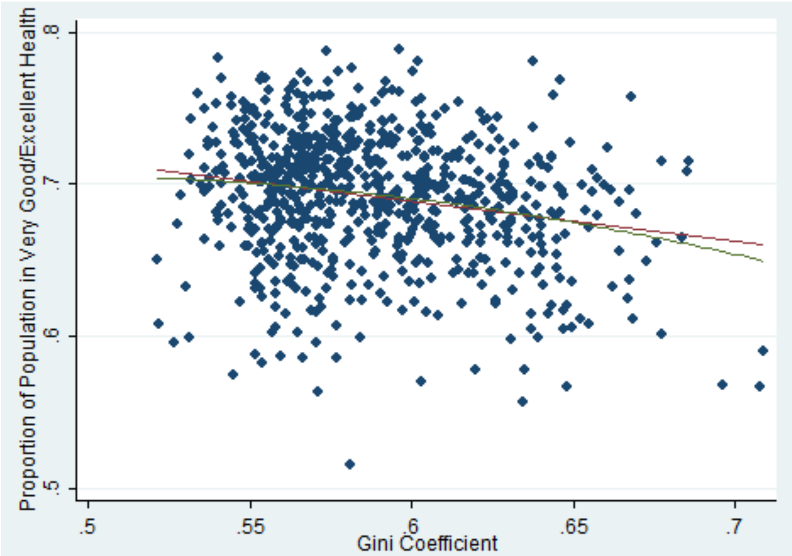
Figure 5 – Proportion of State's Population in Very Good or Excellent Health (across years), 1996-2012



4.5.3 Health Status by Inequality Measure

Figure 6 plots the proportion of populations in excellent health against the top decile. In figure 11, there is a linear and quadratic line of best fit. Both of these lines are almost exactly horizontal. This demonstrates a very weak or non-existing relationship. There does not seem to be much of a relationship, both linear and quadratic without controlling for any covariates.

Figure 6 - Proportion of Population in Very Good or Excellent Health against Gini, from 1996-2012



However, figure 7 and 8 show, by subsampling the data to look at the most equal (least inequality) and least equal (most inequality) states separately. It seems there is some relationship between income inequality and the health of a society. However, the relationship is appears to be fundamentally different at different points in the income inequality distribution. At the low end of the distribution (figure 12), income inequality negatively affects health in a nonlinear fashion. However, the high end of the distribution (figure 13) has a directly opposite relationship. Inequality has a changing relationship with health, depending on a state's pre-existing inequality and this relationship seems to be nonlinear.

Figure 7 - Proportion of Population in Very Good or Excellent Health against Gini for the 5 Most Equal States, from 1996-2012

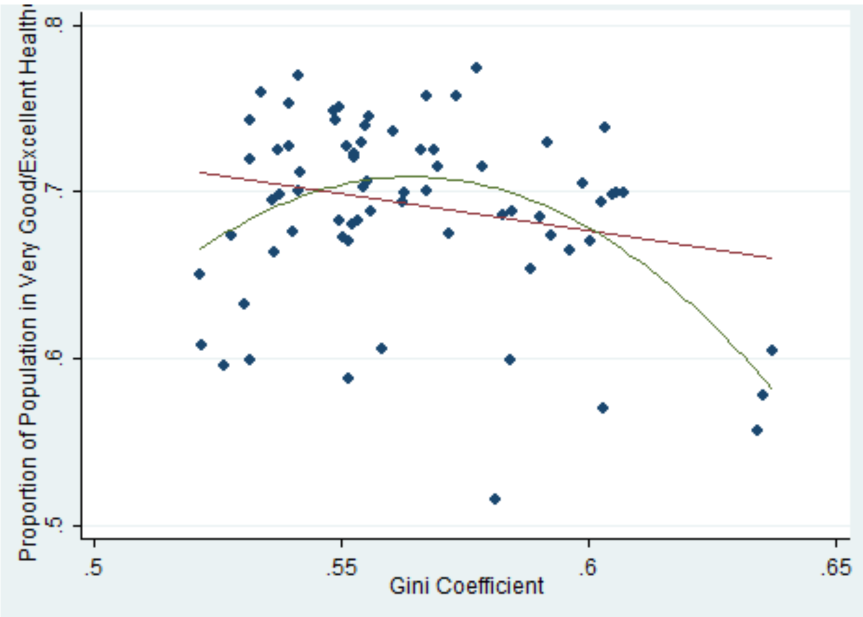
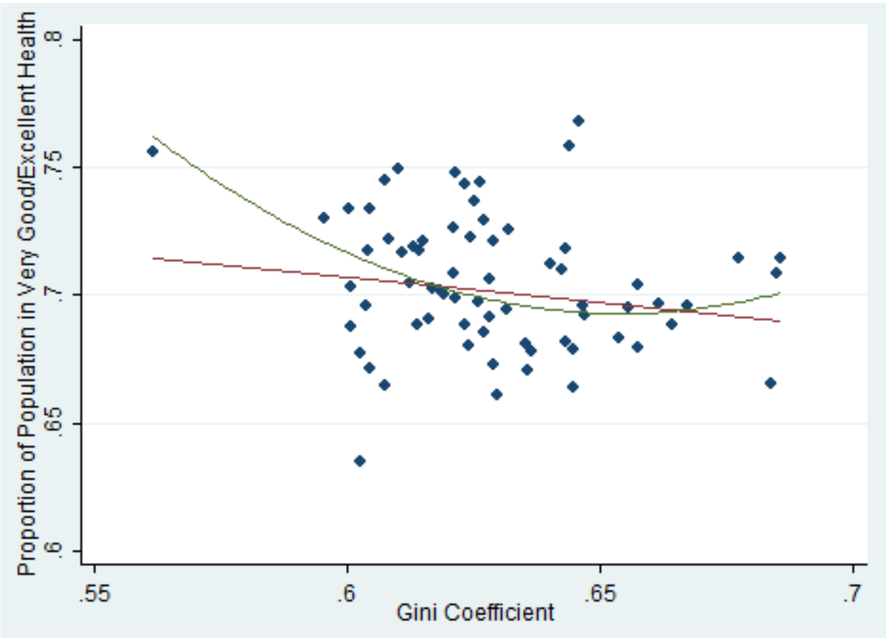


Figure 8 - Proportion of Population in Very Good or Excellent Health against Gini for the 5 Least Equal States, from 1996-2012



5. Results[2]

[2] Results were calculated using the top decile measure, as well as the Gini and Atkinson measure. Regardless of measure used, the results were very similar.

This section will present results from the full sample of data, as well as restricted samples of the five most equal states and five least equal states. The results reported are the marginal effects at the first and third quartile, as well as the mean of each sample's income inequality distribution. These points are chosen to map different sections of the distribution. The hypothesis is the relationship is nonlinear, and as such, we should expect the marginal effects change over the distribution. The quartiles and mean are chosen to find points that are distanced from each other to test this hypothesis (Jantii and Jenkins, 2009).

5.1 Marginal Effects – Full Sample

Table 4 reports the marginal effects from the logit model described in equation 4. The marginal effects are calculated at the mean for all control variables, and the quartile of the distribution for the 2, 3, and 4 year lagged Gini. Column (1) reports the marginal effects for the first quartile, column (2) reports the marginal effects at the mean, and column (3) reports the marginal effects at the third quartile.

Table 4 – Marginal Effects across the Full Sample

Variable	Marginal Effects at 1st Quartile	Marginal Effects at Mean	Marginal Effects at 3rd Quartile
	(1)	(2)	(3)
2 year lagged Gini	-0.65	-0.76	-0.80
	(1.74)	(2.37)	(2.70)
2 year lagged Gini squared	0.55	0.53	0.47
	(2.15)	(2)	(1.61)
3 year lagged Gini	-0.67	-0.77	-0.82
	(1.72)	(2.37)	(2.71)
3 year lagged Gini squared	0.55	0.53	0.48
	(2.15)	(1.99)	(1.61)
4 year lagged Gini	-0.65	-0.74	-0.79
	(1.74)	(2.38)	(2.7)
4 year lagged Gini squared	0.53	0.51	0.46
	(2.15)	(2)	(1.62)

*****,**,* indicate statistical significance at 1,5,10% respectively**

Robust standard errors are presented after being clustered by state

5.2 Marginal Effects – Most and Least Equal States

Table 5 and 6 show the marginal effects for only the 5 most equal (least inequality) and 5 most unequal (most inequality). Column (1) reports the marginal effects for the first quartile, column (2) reports the marginal effects at the mean, and column (3) reports the marginal effects at the third quartile.

Table 5 – Marginal Effects across the 5 Most Equal States

Variable	**Marginal Effects at 1st Quartile**	**Marginal Effects at Mean**	**Marginal Effects at 3rd Quartile**
	(1)	(2)	(3)
2 year lagged Gini	1.32	9.27***	0.44***
	(1.51)	(0.92)	(0.09)
2 year lagged Gini squared	-10.43***	-11.41***	-7.66***
	(1.74)	(0.59)	(0.628)
3 year lagged Gini	1.35	11.15***	0.44***
	(1.55)	(0.99)	(0.099)
3 year lagged Gini squared	-10.4***	-11.40***	-7.67***
	(2.70)	(4.83)	(0.656)
4 year lagged Gini	1.32	11.17***	0.44***
	(1.52)	(0.98)	(0.98)
4 year lagged Gini squared	-10.43***	-11.4***	-7.66***
	(1.76)	(0.59)	(0.63)

*****,**,* indicate statistical significance at 1,5,10% respectively**

Robust standard errors are presented after being clustered by state

Table 6 – Marginal Effects across the 5 Least Equal States

Variable	Marginal Effects at 1st Quartile	Marginal Effects at Mean	Marginal Effects at 3rd Quartile
	(1)	(2)	(3)
2 year lagged Gini	-0.005	-11.98***	-11.74***
	(0.125)	(2.56)	(1.63)
2 year lagged Gini squared	8.28***	7.42***	3.47***
	(1.6)	(1.25)	(0.25)
3 year lagged Gini	-0.006	-11.77***	-11.63***
	(0.01)	(2.69)	(1.74)
3 year lagged Gini squared	8.18***	7.33***	3.45***
	(1.95)	(1.71)	(1.43)
4 year lagged Gini	-0.007	-11.65***	-11.55***
	(0.02)	(2.74)	(1.82)
4 year lagged Gini squared	8.1***	7.26***	3.44***
	(1.69)	(1.35)	(0.25)

*****,**,* indicate statistical significance at 1,5,10% respectively**

Robust standard errors are presented after being clustered by state

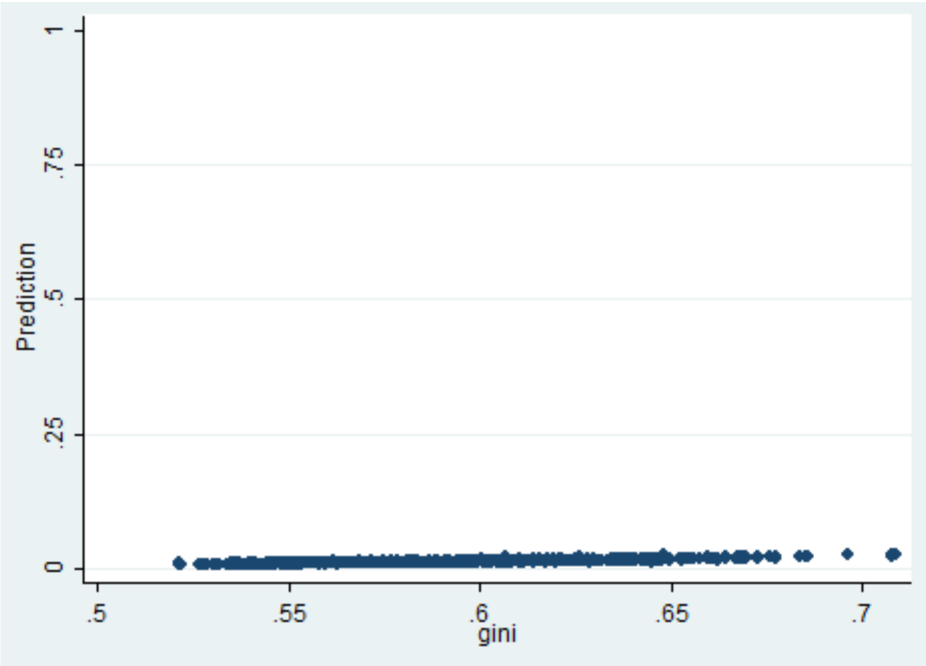
5.2 Discussion of Results in the Full Sample

In the full sample, there is no statistically significant relationship between health and income inequality. Regardless of inequality measure chosen, there is no statistical significance at either the first or third quartile, or the mean of the income inequality distribution.

5.2.1 Discussion of Combined Marginal Effects

Figure 9 shows the marginal effects of the logit model across the entire inequality distribution. The marginal effect line is almost perfectly horizontal. This demonstrates no relationship across the entire sample period. Regardless of where in the income inequality distribution a state is, a slight change leads to no percentage change in the odds an average citizen is in the very good/excellent health group.

Figure 9 – Marginal Effects of the Combined Gini Terms



5.3 Discussion of Results in the Most Equal Sample

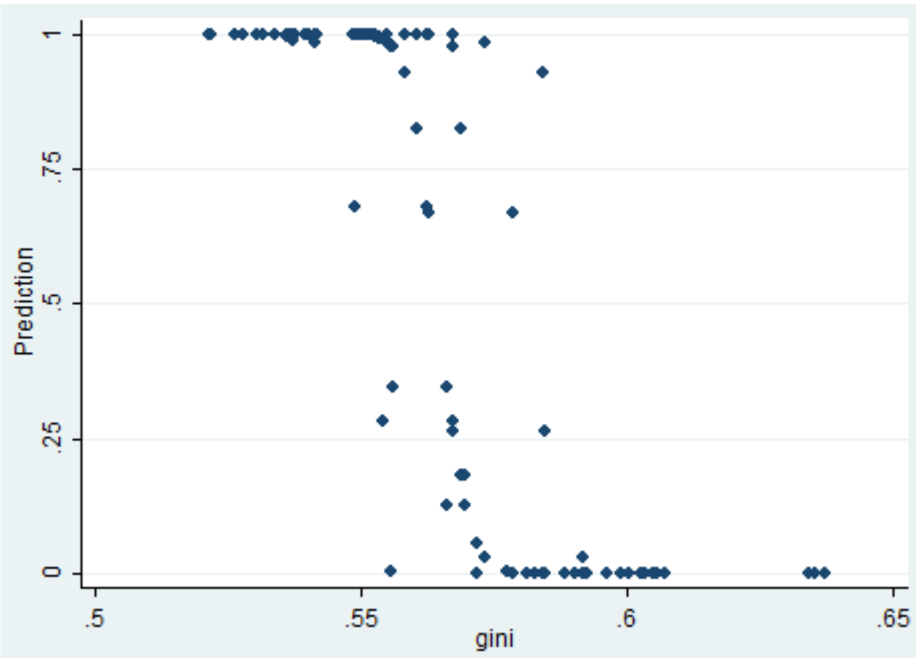
However, if the sample is restricted to either the five most equal states or the five least equal states across the sample period, some significant results start to appear. Not only do we get results that are statistically significant, but are novel as well. Income inequality has a positive nonlinear relationship with health for this sample. Regardless of inequality method used, the sign of the relationship is the same. The level term is always positive, while the quadratic term is always negative. This means the relationship between the two variables is “inverted U” shaped (Figure 7). In these states at the low end of the inequality distribution, increases in the Gini coefficient lead to increases in health. This seems to violate the relative income hypothesis.

Instead of harming health, income inequality increases increase the probability an average citizen is in the very good/excellent health group. The average change in the yearly Gini is 0.003 (the data is coded between 0 and 1). As such, an average increase in the Gini raises the probability of an average citizen in a most equal state at the first quartile of the income inequality distribution by 0.004%. The change in probability for an average citizen in a most equal state at the mean is 0.02%, and at the third quartile is 0.001%.

5.3.1 Discussion of Combined Marginal Effects

Figure 10 shows the marginal effects of the Gini coefficient and the squared Gini coefficient across the income inequality distribution for the five most equal states. For interpretation, the marginal effect change (the y-axis) assumes a unit change in x. However, as the Gini only ranges from 0 to 1, this scale is incorrect. Instead, a unit change in the Gini is 0.01. This changes the scale of the y-axis for all marginal effects graphs from 0 to 0.01 instead of 0 to 1.

Figure 10 – Marginal Effects of the Gini Terms



For the most part, the marginal effect is close to zero. The only portion demonstrating very strong marginal effects only comes in the statistically insignificant portion of the distribution. Otherwise, the marginal effect is very small.

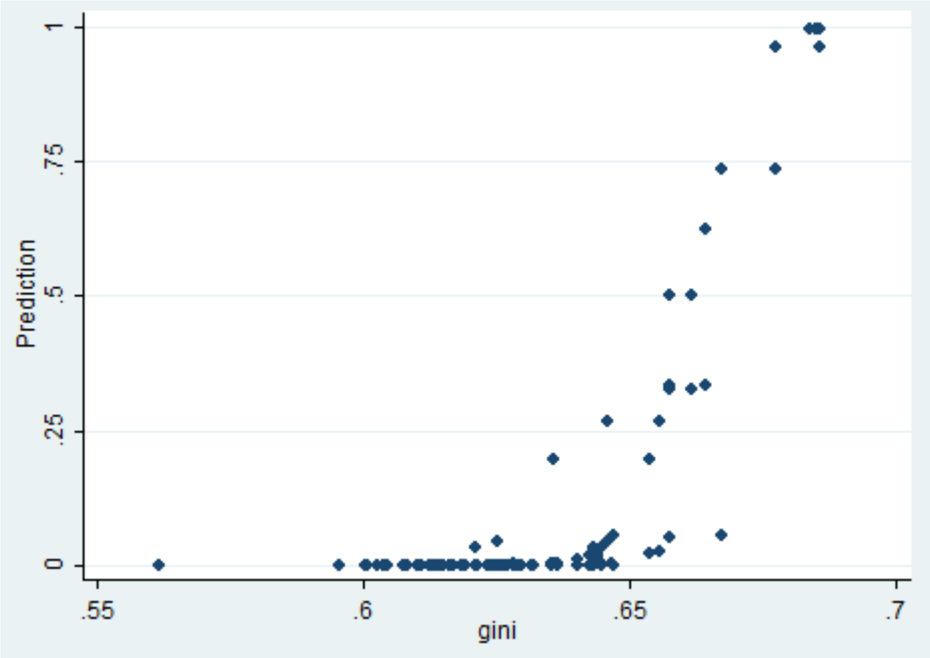
5.4 Discussion of Results in the Least Equal Sample

Truncating the sample to the five least equal states brings significance to most of the inequality measures. An increase in income inequality leads to a decrease in the probability of an average citizen being in the very good/excellent health group. More specifically, an average increase in the Gini (0.003) decreases the probability of an average citizen living in one of the five least equal states (New York, Connecticut, District of Columbia, Florida, and Nevada) at the first quartile by 0.000015%. However, an average citizen living in an unequal state at the mean or the third quartile can expect the probability to decrease by 0.04%.

5.4.1 Discussion of Combined Marginal Effects

Figure 11 shows the combined marginal effects of the Gini coefficient on the least equal states.

Figure 11 – Marginal Effects of the Gini Terms



We see an opposite effect to Figure 10, where the beginning of the distribution has zero effect and as inequality rises, the probability of being in the excellent/very good group increases. Again, the portion demonstrating strong marginal effects only comes from the statistically insignificant portion of the distribution. Otherwise, the marginal effect is very small.

6. Discussion

Two important results come out of the logit model. First, the specific inequality measure does not seem to change results, regardless of sample choice. These robust results demonstrate the results are not a quirk of how a single inequality measure is constructed, but a stronger relationship between income inequality and health. Secondly, income inequality matters more to the health of citizens living in states at either side of the income inequality distribution. In the full sample, the relationship is non-existent. Across the entire distribution, there is no statistically significant relationship. When restricted to either extreme of the distribution, there is a significant relationship. However, this statistically significant relationship is not *economically* meaningful. The marginal effects in the restricted sample are not meaningfully different than zero. While average changes in inequality change the predicted probability of an average citizen, it only changes that probability by a fraction of a percentage point.

6.1 Discussion – Full Sample

Not finding significance across the full sample is fairly standard in the literature. In a survey of papers researching the relative income hypothesis, Wilkinson (2006) found 30% of papers investigating at the state level having little to no evidence of the hypothesis. These findings indicate income inequality does not affect an average person's health regardless of where the state is in the income inequality distribution. The results are robust in the sense removing controls or fixed effects find the inequality coefficients still insignificant, with roughly the same magnitude.

6.2 Discussion – Most and Least Equal States

There may be a few explanations for the positive relationship between income inequality and health in the most equal states sample. While most of the literature finds no relationship or a negative relationship, there is some precedent for a positive relationship. It could be states at the bottom of the income inequality distribution do not receive enough tax revenue (McLeod et al, 2003). The low income inequality could be due to not attracting very rich individuals from unobserved characteristics or by having much more progressive taxation systems. In either scenario, this lower level of government revenue means services not included in the healthcare spending variable (education, infrastructure, welfare, etc.) are not being properly invested into. As such, increasing income inequality could increase tax revenue and benefit average citizen's health. A second explanation is across states, socioeconomic characteristics are heterogeneous and this generates a positive relationship in states with the lowest income inequality (Wen, Browning, & Cagney, 2003). Essentially, citizens in states with more income inequality (to a point) are able to feel a bond with others in their particular neighbourhood. This bond increases social capital within the area and leads to better health outcomes.

The least equal states sample gives the more common results in the literature. Income inequality negatively affects average citizen health. Regardless of inequality measure chosen, the results are economically insignificant, even if they are statistically significant. This truncation demonstrates at least some version of the relative income hypothesis holds. However, the evidence only relates to states at the top end of the income inequality distribution. As well, the evidence presented demonstrates the relative income hypothesis is not linear and homogenous.

7. Conclusion

Using a logit model with clustered standard errors at the state level, this paper found no statistically significant relationship between state level income inequality and individual self-reported health in the full sample. When the sample was restricted to the five most equal or five least equal states, there was a statistical relationship. However, the positive relationship found in the most equal states and negative relationship found in the least equal states have point estimates very close to zero. As such, the results do not support the relative income hypothesis. The relative income hypothesis, that income inequality harms a person's health, may be overstated.

Wilkinson (2006) finds that roughly 70% of papers surveying the United States at different levels of geography find at least some support of the relative income hypothesis. There may be several reasons why this paper does not find support of the relative income hypothesis. This paper uses data that extends past the publication of the Wilkinson survey article. The relationship between income inequality and health may have changed in those additional years. As well, the sample period of 1996-2009 does not have a substantial shock to income inequality or health. This lack of endogenous shocks may not create the right environment to test the relative income hypothesis properly.

The level of geography is an important factor in the relative income hypothesis literature (Subramanian and Kawachi, 2004). The smaller the geographic level of data, the more likely the results will validate the relative income hypothesis. This is due to the main theoretical transmission of income inequality on health. Individuals compare themselves to their peers. The smaller the geographical level, the more accurate these comparisons are. State level data may not be the appropriate level of data to test the relative income hypothesis. County or city data may give stronger evidence of the hypothesis.

Finally, equation identification may be producing these zero magnitude effects. The difference between confounding variables and pathway variables in the relative income hypothesis literature is a fine line. Control variables commonly used in economics (race, education, income, etc.) can also dilute the effect of income inequality on health. This is because there is some evidence that some of these variables (particularly individual income) are transmission mechanisms for income inequality to harm health. It is possible that there is omitted variable bias in the equation that is driving the zero effect.

In conclusion, this paper does not find evidence of the relative income hypothesis at the state level in the United States. Even after restricting the sample to either end of the inequality distribution, the point estimates produced are very close to zero. While there may be some reasons that determine these marginal effects are biased towards zero (as mentioned previously), the results are robust across lag structure of inequality, inequality measure, and sample time period.

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