Master Thesis

Income Inequality Is Everybody's Problem.

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Abstract

The research presented here demonstrates that there is a *spillover effect* of income inequality on society at large. This means that not only the lowest incomes are confronted by income inequality. This research shows that even people with higher incomes, living in a state with higher income inequality, have lower self-assessed mental and physical health than people living in a state with less income inequality. The main research question is: "*To what extent does a spillover effect, caused by income inequality, exist in the United States?".* The research focuses on the context of the United States, California and Orange County and makes use of various quantitative methods to answer this main research question.

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Acknowledgements

At the moment I am writing this, a turning point in my life will start. Finishing this Master's thesis means finishing my student life. After one Bachelor and two Masters at the University of Groningen, writing these acknowledgments means the last piece of work of my student life.

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I hope you will enjoy reading my thesis.

All the best,

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1. Introduction

Life expectancy in Sweden is higher than that of the United States. In Louisiana, a higher percentage of children drops out of school than in Utah. In the United Kingdom, there are relatively more people with a mental illness than in Japan. And in Alabama, there are proportionally more homicides than in Wisconsin. What is the explanation for these differences? According to Wilkinson and Pickett (2010) and several other authors, *income inequality* is an important answer. In their book, "*The Spirit Level – Why Equality is Better for Everyone*" (2010), insight is provided in the relation between income inequality and a wide range of socioeconomic and psychosocial factors. The findings of Wilkinson and Pickett show for example that levels of mental and physical health, levels of trust and social cohesion and educational attainment are lower in countries and American states where income inequality is higher. Income inequality has influence on a wide range of factors. Ballas (2013) claims that income inequality is associated with several health and social problems. Evidence of a relationship between income inequality and mental health, trust, community life and child well-being has been found. Income inequality is linked to the social and geographical context of an individual, and this context is associated with a wide range of factors. People compare their own situation with other people in their social and geographical context. These social comparisons between people result in frustration, status anxiety, and stress (Wilkinson and Pickett, 2010). Therefore, income inequality affects the quality of life and wellbeing in cities. Furthermore, Kawachi and Kennedy (1999) claim that income inequality is associated with disinvestment in human capital, erosion of social capital and social comparisons. When inequality between people is too high, people have less eye for each other. Other consequences of a high level of income inequality are mentioned by Thorbecke and Charumilind (2002), Wilkinson and Pickett (2010), Lynch et al. (2000) and Kawachi and Kennedy (1997) who claim that income inequality affects (mental) health education performance, teenage births, homicides, imprisonment rates, social mobility, obesity, life expectancy, infant mortality, political and social conflicts, crime, social cohesion and trust between people in cities and neighborhoods.

Various research has been conducted to get insight into the factors that determine well-being and health. A key research study by Oswald and Wu (2009) examined the predictors of well-being in the United States. The dependent variables they used, in order to get insight in well-being are: *life satisfaction* and *mental distress*. By carrying out suitable regression analyses, their research shows that these two variables have a significant relationship with the income levels of people, the state where someone is living, the employment state of someone and the educational level of someone. In addition to these findings, this research also attempts to find out if *income inequality* is a factor that matters with regards to well-being and health.

As mentioned, the book "*The Spirit Level – Why Equality is Better for Everyone*" by Wilkinson and Pickett (2010) gives a comprehensive insight into the influence of income inequality on a wide range of factors. The focus of this book is on the inequality level of countries and American states. The analysis has been conducted with the observance of income inequality at the level of countries and states. However, Ballas (2013) claims that people compare their own situation with other people in their social and geographical context, which indicates that at lower geographical levels people are in a higher extent affected by income inequality. Lower geographical levels are not taken into account in the book of Wilkinson and Pickett and also other research does not show the relationship between income inequality and wellbeing and health at lower geographical levels. The research presented here adds a spatial component to the findings of Wilkinson and Pickett by analyzing the influence of income inequality at the level of counties in California and cities in Orange County. Analyses have been carried out, in this research, to find out if the level of income inequality matters at the level of states, counties and cities.

At first glance, people might think that income inequality affects only people from the lowest income groups. However, Kawachi and Kennedy (1997) state that income inequality has a spillover effect on the quality of life, experienced by a diversified group of people; even by people who are not part of the lowest income percentiles. A high level of income inequality causes lower social cohesion and decreasing trust between people in cities and neighborhoods. According to these authors, reducing income inequality offers the prospect of greater social cohesiveness and better population health. They argue that, because of this lower social cohesion and decreasing trust, income inequality affects the whole society, not only people from the lower income classes. In short, a spillover effect means that not only the poor incomes experience negative outcomes due to income inequality, but also people with higher incomes. In line of thought with the concept of the spillover effect, income inequality affects people from lower *and* higher income groups. This is in line with findings of Lynch et al. (2004), Kondo et al. (2009) and Wilkinson and Pickett (2010) who claim that income inequality affects the *whole* society, across different income groups. Research has been conducted to get insight in this spillover effect. In contrast to these authors who focused on the population as a whole, this research focuses on the effects of income inequality on mental and physical health levels, across different income levels separately. This kind of analysis provides an indication to what extent people with higher incomes are affected by the level of income inequality in the state where they live. This provides a meaningful insight in the existence of a spillover-effect.

In the specific context of *Orange Country,* California, the distribution of income is considered a major challenge. This is mentioned by Doti and Horowitz, who wrote an article on the website OC-Register (2018). They mention that since the 1980s, by almost any measure, income inequality has worsened in Orange County. Household income in Orange County was 7.5 times greater in the 90th income percentile as compared to the 10th income percentile of the population, in 1990. However, by 2014, that ratio increased to 11, what shows that the income gap between rich and poor is increasing in Orange County. An explanation of this trend, which Doti and Horowitz give, is the widening gap between earnings of people who graduated high school and people who graduated college. Besides, the authors explain that considerably less Hispanics graduate college, what suggests that inequality in income distribution also follows closely along ethnic lines. Orange County recovered well after the financial crisis of last decade and the number of jobs in the region is growing. A striking point about this, mentioned by Roosvelt (2016), is that this job growth is ‘highly polarized’, and to a limited extent oriented on the lower income groups.

These income differences stand out in Orange Country. In figure 2, an overview is given of the percentages of the different household income percentiles in Orange County.

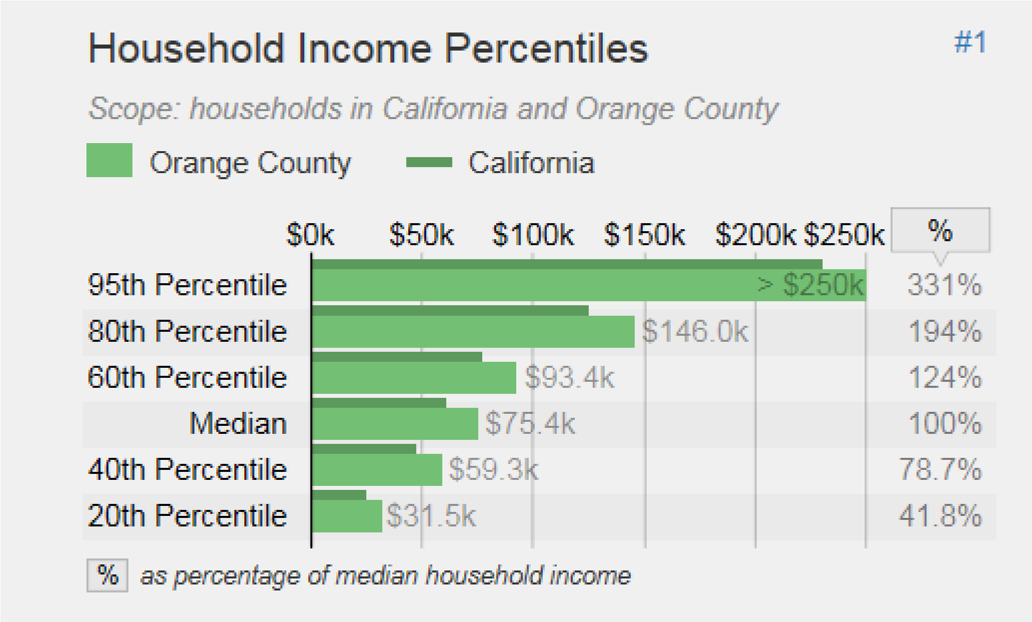

Figure 1. Household income percentiles in Orange County (Statistic Atlas, 2105).

Looking at this figure, it strongly becomes clear that income differences in the Orange County are more severe than the income differences in the state of California as a whole, where the levels of income inequality are more severe than in the whole of the United States (US Census Bureau, 2018). The gap between the poorest and richest is striking in Orange County. An ‘underclass’ may arise in Orange County, caused by the strong income gaps.

1.1. Problem Definition

The research presented here is focusing on the level of income inequality in Orange County, California and the United States and the influence this has on the well-being and health levels. The main focus of this thesis is on the ‘*spillover effects*’, caused by income inequality. As is apparent, the income inequality in Orange County is severe and increasing. Several authors show that income inequality is related to a number of socioeconomic and psychosocial factors. The relationship between income inequality in Orange County, California and the United States and the level of mental and physical health is analyzed in this master thesis. These effects are related to their geographical scale level, and to the level of income inequality at this geographical scale level. This first analysis is focused on the effects at Census Tract-level (neighborhood-level) and the impact of income inequality at different geographical levels on the aggregate of these Census Tracts. Another analysis has been conducted, based on income inequality and income levels of American states. This analysis concerns the question to what extent a spillover effect exists. Finding out to what extent a spillover effects exists is the main objective of this research.

1.2. Research Questions

This thesis focuses on the following main research question:

- To what extent does a spillover effect, caused by income inequality, exist in the United States?

To answer this research question, three sub questions are drawn up:

- What is the degree of income inequality *between* and *within* different geographical scale levels in Orange County, California and the United States?

- What are the socio-economic and psychosocial consequences of income inequality in the context of Orange County, California and the United States?
- To what extent are the social-economic and psychological consequences of income inequality related to their geographical context?

1.3. Data and Methods

The research conducted in the context of this thesis employed several methods. In order to get insight in income inequality and all its related aspects, a theoretical framework has been drawn up which forms the framework of the further empirical research. This empirical research exists of three different parts, and three different data sources are used. The first part provides insight into the level of income inequality between different parts of Orange County, California and the United States. Data provided by the U.S. Census are used in order to get this overview of income inequality levels. Then, an analysis has been conducted to get insight in the relationship between health related factors, income inequality and several other socio-economics factors. In this analysis, the geographical context of this relationship is taken into account. A multilevel analysis has been carried out in order get insight in this geographical context. The data used in this analyses are at the Census Tract-level, which is similar to a neighborhood level. The data used in the analyses are the averages for all these Census Tracts. The impact of the geographical context, income inequality and other predictors on health-levels on the aggregate of the analysis are analyzed. Data provided by the 500 Cities Project and the U.S. Census are used to carry out this analysis. A last analysis has been conducted in order to get insight in the so-called spillover effect. Several Tobit-regressions have been carried out to find out to what extent this spillover effect exists. Data provided by the BRFSS and the U.S. Census are used in order to fulfill this. A more comprehensive overview of the methods that are used in this research can be found in the third section of this thesis, which explains the methodology.

1.4. Thesis structure

The following section of this thesis consist of the theoretical framework. In the theoretical framework, articles with regard to income inequality and the spillover effects are analyzed and discussed. After this, the methodology of this research is explained. The United States, California and Orange County as study area are discussed and the way data are collected and analyzed are described in this section. Subsequently, the outcomes of the data collection are discussed and analyzed in the fourth section. In the last section, a discussion is drawn up, based on the theoretical framework and data analysis. Finally, the outcomes of the research are concluded.

2. Theoretical Framework

A theoretical framework has been established which forms the basis for the empirical research. This theoretical framework analyzes and discusses international articles in the field of income inequality. The first subsection elaborates on *income* and *wealth* inequality. Both phenomena are described, distinguished, and related aspects are explained. The second subsection focuses on the measurability of income inequality, and several ways to measure income inequality are explained. After this, several trends of income inequality are being explained in the third subsection. Then, the socioeconomic impacts of income inequality are discussed in the fourth subsection. The spillover effect, as described in the introduction, is addressed in the fifth subsection. The sixth subsection focuses on the role of institutions and governments with regard to income inequality. In addition to income inequality, several other factors also affect the health and well-being levels of individuals. These factors are discussed in the seventh subsection. In the last subsection of the theoretical framework, a conceptual framework and a short summary of the theoretical framework have been made up.

2.1. Income and Wealth Inequality

Income inequality is described as the income distribution expressible as a function of inequality *between* nations or societies and inequality *within* nations or societies (Cowell and Jenkins, 1995). Cowell and Jenkins mention that this description could be applied on a smaller scale which may involve inequality within and between constituent subgroups of the population of a particular country. This addition to the description indicates that income inequality may be considered from different geographical perspectives. Wilkinson and Pickett (2010), who elaborated in their book "The Spirit Level – Why Equality is Better for Everyone" on the psychosocial consequences of income inequality, mention that people are affected very differently by income inequality within a society from the way people are affected by income differences between societies. Based on comparisons between different societies, they claim that social problems in societies have little or no relation to levels of *average* incomes in a society. However, *within* these societies, social problems are closely related to income. People with higher incomes within a society tend to have a higher level of well-being and a better health level than people with lower incomes. According to Wilkinson and Pickett, average levels of income or living standards in societies do not matter at all, but income differences within a society do. Even more so, the overall burden of these social and health problems is much higher in societies with higher income differences. The authors give two possible explanations for this finding. One explanation is that people within a society compare themselves with other people within the society. It may matter if someone is doing better or worse than someone else in his or her proximity. People do not want to be inferior to other people in their society. This explanation shows that *relative income* is significant, which is in line with the finding of Marmot and Wilkinson (2001) who claim that in rich countries, wellbeing is more closely related to relative income than to absolute income. Another explanation is given from the perspective of social mobility. Due to income inequality, there are differences in the level of social mobility within a society, which sorts healthy from the unhealthy people. Wilkinson and Pickett explain that the healthy have the capacity to move up the social ladder whereas the unhealthy end up at the bottom. The authors state that material inequality matters and that this may result in social status differences in culture and behavior within a society. These differences are reflected by gradients in health and social problems.

An important addition to the findings of Wilkinson and Pickett (2010), described above is that it matters in which context income inequality is analyzed. In 2006, Wilkinson and Picket wrote an article about the relationship between income inequality and population health, and mentioned that income differences which are called absolute in one context could be called relative in another. The level of income inequality within a particular large area may be broken down into levels of inequality within and between constituent areas at a lower geographical scale level, within that area. Wilkinson and Pickett explain that when more and smaller constituent areas are used, the more of the income inequality gets converted into income differences *between* these different areas and the less of the income inequality remains *within* the areas. The authors mention that this conversion can be done *ad infinitum.* In the ultimate scenario, income inequality is analyzed between the smallest (single households) areas. This insight makes clear that it is important to be aware about the level on which someone is analyzing income inequality and what this explains about the level of income inequality *between* different areas and *within* a particular area.

An important assumption about income inequality is that it is strongly influenced by *institutions.* Fortin and Lemieux (1997) analyzed the impact of institutions and governments on income inequality in the last decades, and concluded that institutional forces cannot be overlooked in any serious attempt to understand rises and falls in income inequality. Institutions or governments often alter the level of income inequality due to taxation policy, social security benefits, income transfers, investment incentives and other mechanisms (Kaplan, 1996). These governments and institutions operate at different scale levels and therefore spatial differences exist with regards to income inequality.

A broader way to approach inequality could be done from the perspective of *wealth inequality*. Wealth is about *ownership* and is not by definition the outcome of income (Keister, 2000). For example, wealth can be generated by family possession or earned income in the past. Wealth is defined by Keister as the net worth of total assets minus total liabilities of a single person. Therefore, wealth and income should not be considered as equivalents. In contrast to income, defined as a *flow* by Keister, wealth is defined as the *stock* of resources at a particular point in time. The author explains that wealth is more unequally distributed across the population than income in the United States. This thesis chooses to focus mainly on income inequality, due to the availability of data about income levels and income inequality at low geographical levels, such as Census Tracts and cities. However, the distinction between wealth and income inequality must be considered in this research.

There is a number of methods to measure income inequality. These measures seek to represent the allocation of income of a particular population (Lynch et al., 1998). Different measures to get insight in income inequality are discussed in subsection 2.2.

2.2. Measuring Income Inequality

In this subsection ways to measure income distribution and inequality at a particular location are discussed. Measuring inequality is an important tool to conduct this research. There exist different ways to measure income distribution and inequality. De Maio wrote an article in 2007 about these different measures, in which he explains ways to implement and interpret these measures. For this research, the Gini-Coefficient has been chosen to use as measure, because it measures income inequality across the whole society. Besides, Gini is chosen because of its interpretation, the Gini coefficient is easily interpretable and comparable. These arguments are more elaborately explained in the next subsection. Another argument to use the Gini-coefficient is because of accessible data where Gini is used as measure of income inequality. However, other measures have also been considered to be used. These measures are described in subsection 2.2.2.

2.2.1. Gini-Coefficient

The measure to operationalize income inequality that is used in most cases, is the *Gini-coefficient*. The Gini-coefficient is derived from the *Lorenz-curve* framework (De Maio, 2007). This framework is shown in figure 3. De Maio explains that the Lorenz-curve shows the percentage of total income earned by cumulative percentage of the population. This means that in a perfectly equal society, the poorest 30 per cent of the population, for example, would earn 30 per cent of the total income, and the poorest 60 per cent of the population would earn 60 per cent of the total income. In this case, the Lorenz curve would follow the 45 degree line of equality. When the income distribution is less equal, the Lorenz-curve deviates from the line of equality and moves toward point B (figure 3). In this case, the poorest 30 percent may earn 20 per cent of the total income and the poorest 60 per cent may earn 40 per cent of the total income. The following step is to determine the Gini-coefficient. De Maio explains that the coefficient is equivalent to the size of the area between the Lorenz-curve and the 45 degrees line of equality, divided by the total area under the 45 degrees line of equality. This calculation yields a number between 0 and 1. A Gini-coefficient of 0 represents a society in which the income is perfectly equally distributed. On the other hand, a Gini-coefficient of 1 represents a society wherein all income is earned by one single person.

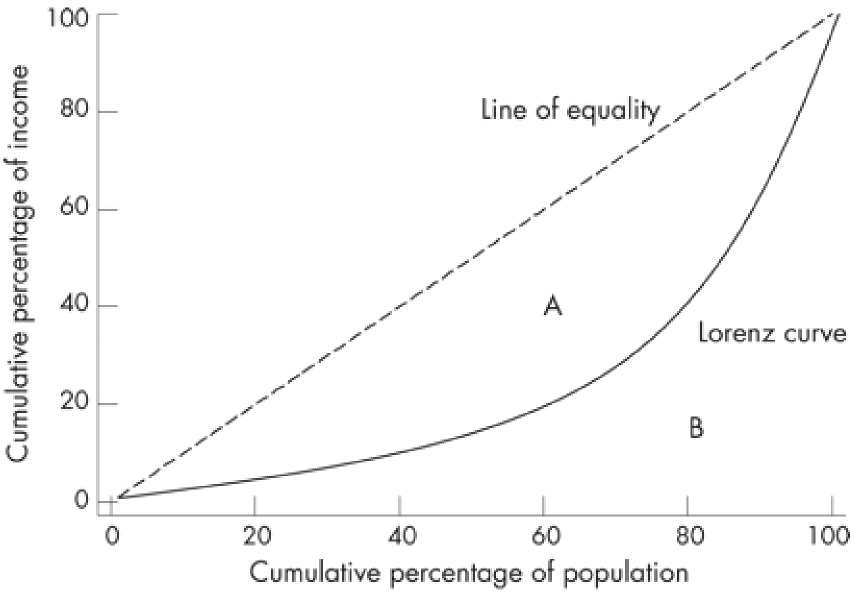

Figure 3. The Lorenz-curve framework (De Maio, 2007).

An important strength of this Gini-coefficient is the interpretation. The Gini-coefficient shows a number between 0 and 1 and is therefore easily interpretable and comparable to other regions or countries (Chen et al. 1982). Another strength of the Gini-Coefficient is that it measures income inequality across the whole society, rather than comparing the extremes of the society (Wilkinson and Pickett, 2010). A weakness of the Gini-coefficient, according to De Maio (2007), is that it is incapable of differentiating sorts of inequality. He mentions that different Lorenz-curves may intersect, reflect different patterns, but result in a similar Gini-coefficient. De Maio explains that this results in high sensitivity to inequalities in incomes in the middle of the income spectrum.

2.2.2. *Other Measures*

Another measure for income inequality is the *Atkinson index.* The Atkinson index incorporates a sensitivity parameter (Ɛ), which can range from 0 to infinity. (De Maio, 2007). This index allows for different levels of sensitivity to inequalities in different parts of the income distribution. When the index has a value of 0, the researcher is indifferent about the nature of the income distribution. De Maio explains that when the value is higher, the more sensitive the Atkinson index becomes to inequalities at the bottom of the income distribution. Similar to the Atkinson index, the *GE-Index* also incorporates a sensitivity parameter (α) which differs in the magnitude given to inequalities in differing parts of the income spectrum (De Maio, 2007). The more positive α is, the more sensitive the index is to income inequalities at the top of the income distribution. On the other hand, the closer to zero α is, the more sensitive the index is to inequalities at the bottom of the income distribution (Coulter et al. 1992). The range of the values of this index is from 0 to infinity. A value of 0 represents a state of equal distribution, and higher values than 0 represent increasing levels of inequality.

A fourth way to measure income inequality is the calculation of *decile ratios*. De Maio (2007) explains that this calculation is conducted by taking the total income earned by, for example, the 10 per cent of people who earn the most, and divide this total income by the income earned by the 10 per cent of people who earn the least in a particular area. A last measure that is discussed is the *Robin Hood Index*, also known as the *Pietra Index.* This index represents the maximum vertical distance from the Lorenz curve (figure 3) to the 45 degrees line of equality (De Maio, 2007). This index can be interpreted as the share of income that has to be transferred from the incomes above the average to the income below the average in order to obtain an equal income distribution. A higher Robin Hood Index value implies a more unequal society, wherein a higher proportion of the total income needs to be transferred to achieve equal income distribution.

2.3. Trends in income inequality

This subsection elaborates on the income inequality trends of the last decades. Several patterns that came forward in the last decades are clarified. Cingano (2014) mentions that in most OECD countries, the gap between rich and poor is at the highest level since 30 years. At the moment Cingano wrote his article, the richest 10 per cent of the population of the OECD earned 9.5 times the income of the poorest 10 per cent, while in the 80s this ratio stood at 7:1 and this ratio has been rising continuously over time. The only period this income inequality increase was interrupted was during the first years of the 'Great Recession' between the late 2000s and early 2010s. Cingano explains that this increasing income inequality is not only caused by the increasing top income shares. He states that also incomes at the bottom grew much slower during the prosperous years and fell during the economic downturns. It stands out that until the Great Recession the average real household incomes increased by 1,6 per cent annually in all OECD countries. However, Cingano explains that in three quarters of the OECD countries the incomes of the top 10 per cent grew faster than the incomes of the poorest 10 per cent. A changing trend occurred after the Great Recession when incomes stagnated or even fell in most countries. This trend occurred particularly in Spain, Ireland, Iceland and Greece, where the incomes fell by more than 3,5 per cent per year. In the countries where the incomes fell, the incomes of the bottom 10 per cent fell more rapidly, and in half of the countries where the incomes continued to grow, the richest 10 per cent did better than the poorest 10 per cent of the population. An important note, mentioned by Cingano, is that the income inequality ratios widely vary across OECD countries. The ratio is relatively low in the Nordic and Continental European countries. Higher levels of income inequality can be found in for example Greece, Israel, Italy, Japan, Korea, Mexico, Portugal, Turkey, United Kingdom and the United States. An overview of the increasing income inequality between 1985 and 2011 or later (latest available data) is shown in figure 4. In this figure the Gini-coefficient is used as measure for income inequality.

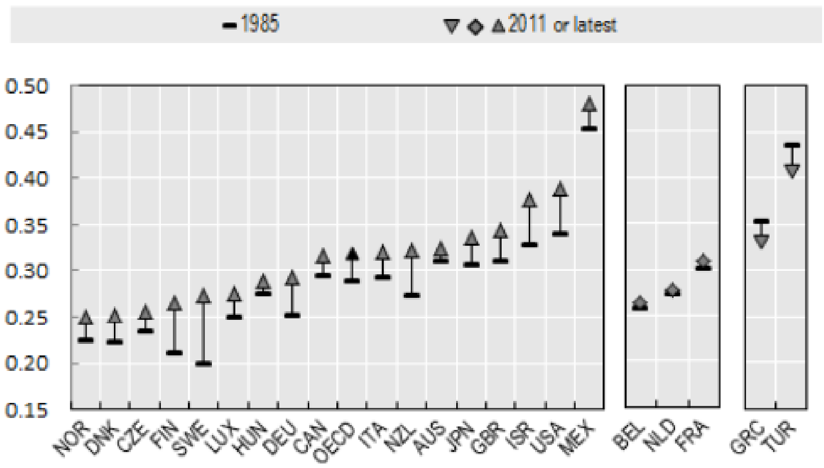

Figure 4. Gini Coefficient of OECD Countries in 1975 and 2011 or later (Cingano, 2014).

Figure 4 shows that in most OECD Countries the income inequality increased from the 80s. However, there are some exceptions. In Belgium, Netherlands and France, the income inequality remained constant from the 80s and it comes forward that in Greece and Turkey the income inequality decreased.

Two major trends in income inequality are discussed by Alderson and Nielsen (2000). They focused on income inequality during the 20th century and explain that two major trends come forward: the “Kuznets-curve” and the “great U-turn”. The Kuznets hypothesis suggests that for societies at a relatively high level of development there exists a negative relationship between development and inequality. According to the Kuznets hypothesis, there exists a curvilinear, inverted U-shaped relationship between development and inequality. The authors explain that when there is long-term industrial development, inequality increases initially, then peaks and levels off and at the end income inequality declines. This link is explained by a possible causal relation from economic growth to income distribution (Galor & Tsiddon, 1996). This causal relation assumes that there is a more equal distribution of income and human capital in a later stage of economic growth. According to the Kuznets-curve hypothesis, lower incomes only benefit from economic development in the longer term. In contrast to the Kuznets-curve, several industrial societies experience a radical reversal of Kuznets’ hypothesis. An example of this is the increasing income inequality in the United States since the 70s after four decades of moderating inequality (Alderson & Nielsen, 2000). Since the 70s, income inequality grew in a steady state in the United States. This phenomenon is described as the great U-turn. Alderson and Nielsen explain the great U-turn in line with increasing unemployment caused by migration, automation of jobs and the changing socioeconomic position of elderly. This results in less employment which results in more income inequality. Another important aspect these authors mention as reason for the great U-turn from the 70s is the increasing globalization. Alderson and Nielsen elaborate on the impact of direct investments on income inequality and explain that the international competition and increasing direct investments also results in less employment and more income inequality. Another reason for the increasing income inequality is the growth in incomes shares of the richest 5 per cent of the population since the 80s (Piketty & Saez, 2006). Between 1979 and 2006 the incomes shares of the 5 per cent richest populations increased by 50 per cent with a substantial portion of the increase occurring in the 2000. While these top incomes increased during this period, the incomes of the median and lower households barely changed (McCall & Percheski, 2010).

In addition to the increasing income inequality from the 1970s, wealth inequality increased even more. Wealth, described by Stone et al. (2018) as the value of a household's property and financial assets minus the value of its debts, is distributed less evenly than income. Stone et al. state that the share of wealth held by the top 1 per cent increased from 30 per cent in 1989 to approximately 49 per cent in 2016. In contrast, the share owned by the bottom 90 per cent decreased from 33 per cent in 1989 to nearly 23 per cent in 2016. Saez and Zucman (2016) elaborate on several drivers of the increasing wealth inequality. The key driver, according to them, is the upsurge of top incomes. They claim that income inequality has a snowballing effect on the distribution of wealth. The authors explain that top incomes are being saved at high rates, which in turn pushes up the wealth concentration. Saez and Zucman explain that this is an important driver of wealth inequality since the 1980s. The second driver of increasing wealth inequality is in line with the first driver. The authors explain that since the 1980s there is a fall in middle-class savings which may owe to the low growth of middle-class wealth. Other reasons, mentioned by Suez and Zucman are more behavioral in nature. They mention that increasing wealth inequality is also caused by predatory lending or by growing behavioral biases in saving choices of the middle-class.

2.4. Socio-Economic and Psycho-Social Impacts of Income Inequality

As mentioned in the introduction, several authors show that income differences affect a wide range of socio-economic and psychosocial factors. Ballas (2013) presents an overview of studies that demonstrate a relation between large income differences and mental health, trust, community life and child well-being. Other consequences of large income differences between people are mentioned by Thorbecke and Charumilind (2002), Wilkinson and Pickett (2010), Lynch et al. (2000) and Kawachi and Kennedy (1997) who state that income inequality negatively affects (mental) health, education performance, social mobility, life expectancy, social cohesion and trust between people in cities and neighborhoods. Besides, these authors claim that income inequality increases the level of teenage births, homicides, imprisonment rates, obesity, infant mortality, political and social conflicts and crime.

Income inequality is linked to the social and geographical context of an individual, and this context is associated with a wide range of factors (Ballas, 2013). People compare their own situation with other people in their social and geographical context. Therefore, income inequality affects the quality of life and wellbeing at a particular place. This finding is in line with the finding of Lynch et al. (2000) who elaborate on the psychological environment. They state that psychological factors are paramount in understanding the health effects caused by income inequality. They refer to Wilkinson (1997) who argued that income inequality has influence on health due to perceptions of place in the social hierarchy based on relative position of income. This relative position results in perceptions that produce negative emotions, such as shame and distrust. Lynch et al. (2000) explain that these negative emotions are translated "inside" the body into poorer health, via psycho-neuro-endocrine mechanisms and stress induced behaviors. The authors explain that simultaneously these perceptions, caused by the relative position of an individual, are translated "outside" into antisocial behavior, reduced civic participation, and less social capital and engagement within the community. According to this way of thinking, perceptions of social rank, caused by income differences, have negative biological consequences for individuals and negative social consequences for interaction between individuals. These findings by Lynch et al. have strong links with the findings of Wilkinson and Pickett (2010), who elaborated in their book "The Spirit Level - Why Equality is Better for Everyone" on the psychosocial and socio-economic consequences of income inequality. They claim that greater inequality seems to raise people's social evaluation by heightening the relevance of social status. People come to see social position as a more important aspect of their identity. They explain that increasing inequality is linked to status competition which results in status 'anxiety'. These insights correspond with the ideas of subsection 2.1. where it stood out that *average* income levels in societies are not explaining many social problems, in contrast to large income differences *within* a society, what is considered as an important cause of many social problems. Income inequality is a context-related phenomenon, which means that individuals consider it from the perspective of their environment.

Another reason that may explain the influence of income inequality on social problems, experienced by people lower at the social-economic ladder is the level of 'control'. Adler et al. (1994) claim that there is evidence that experience of control contributed to lower morbidity and mortality. They state that individuals higher on the income ladder could have more frequent or more significant possibilities to influence the events that affect their lives, in contrast to individuals with lower incomes. Adler et al. state that this sense of control could affect education, occupation, housing, nutrition, health behaviors, medical care and other aspects of social class experience. This way of thinking reasons the emergence of social problems by income inequality in terms of possibilities and control that people from different income classes have.

In the book by Wilkinson and Pickett (2010), insight is given in the relation between income inequality and a wide range of socioeconomic and psychosocial factors. The remainder of this subsection consists of the relationship between income inequality and individual socio-economic and psychosocial factors. This analysis has been carried out with reference to *The Spirit Level* and several other scientific articles.

2.4.1. Income Inequality, Education and Opportunities

This subsection elaborates on the relationship between income inequality and education and the opportunities people have. Various authors assume that income inequality forms a framework that strongly influences educational attainment, social mobility and future opportunities. Corak (2013), for example, mentions that in a place with a high level of income inequality, in the present, it is more likely that the family background determine the future earnings of an individual, than in a place where income inequality is limited. In places with larger income differences, one's own hard work plays a commensurately weaker role. Corak elaborates on *intergenerational* mobility which deals with mobility across generations, and he shows that in countries with a high degree of income inequality, earnings of parents determine future earning of children more than in country with a lower degree of income inequality. Andrews and Leigh (2008) conducted a cross-country analysis and had a similar outcome. Based on their analysis, they conclude that in more unequal countries it is harder to climb up the income ladder than in equal countries. This is similar to the findings by Wilkinson and Pickett (2010) who dedicated two chapters in their book on the relationship between income inequality and educational attainment, and income inequality and social mobility. The possibility of *social mobility* is described by Wilksinon and Pickett as the *equality of opportunity*, which means that anybody has the opportunity to achieve a better economic or social position for themselves and their family, by their own merits and hard work. An important measure to analyze social mobility is *income mobility*, which shows the extent to which people's incomes change during their lifetimes, or how much they earn compared to their parents. Based on longitudinal studies in eight countries, Wilkinson and Pickett show that the relationship between intergenerational and social mobility and income inequality is strong. Later in this subsection the evidence of this relationship is discussed. An important reason for this strong relationship is the public money spent on *education.* Education is considered as the main engine of social mobility in developed countries, according to the authors. In line with this, Wilkinson and Pickett state that more unequal countries have worse educational attainment. Even more so, children in more unequal states are more likely to drop out of school. Blanden and Gregg (2004) conducted a similar analysis and state that income inequality among families with children leads to increased inequalities in educational attainment.

There are various mechanisms that provide explanation about the influence of income inequality on educational attainment. A factor that influences this relationship is the public expenditure on education. Wilkinson and Pickett claim, based on a cross-country analysis, that public expenditure on education is strongly linked to the level of income inequality. *Environmental* factors are also determining for the educational attainment, according to Wilkinson and Pickett. They explain that a stimulating, safe and responsive environment is essential for early learning. Such an environment is harder to create when parents are poor, stressed or unsupported. People feel more happy and confident in a stimulating environment which, according to Wilkinson and Pickett, makes an important contribution to learning and memory. Blanden and Gregg (2004) agree with this point of view and mention that the quality of childcare, the home environment, social activities, neighborhood and schools, all factors linked to the income and social class of parents, have an important influence on the educational outcomes and life chances of children. Another way inequality affects educational achievement is through the impact on aspirations, norms and values of people who are lower down the social hierarchy. Wilkinson and Pickett explain that education is generally considered by the middle and higher classes as the way to climb upward the social ladder. These values might not always be subscribed to by the lower social classes. In reality, however, this does not appear to be fully the case. Wilkinson and Pickett demonstrate on the basis of a cross-country analysis that the aspirations are relatively high in countries with large income disparities. This is caused by the stigma on badly paid professions. However, there appears to be a gap between the aspirations and reality which leads to frustration and disappointment.

As mentioned, a strong relationship is shown between social mobility and income inequality. Data about income inequality and social mobility are shown in figure 5. Wilkinson and Pickett used data from a study by Blanden et al. (2005). These researchers used longitudinal data and were able to calculate social mobility as the correlation between father's incomes at the moment their sons were born and the incomes of the sons at age thirty. Figure 5 shows that countries with a higher level of income inequality have lower social mobility.

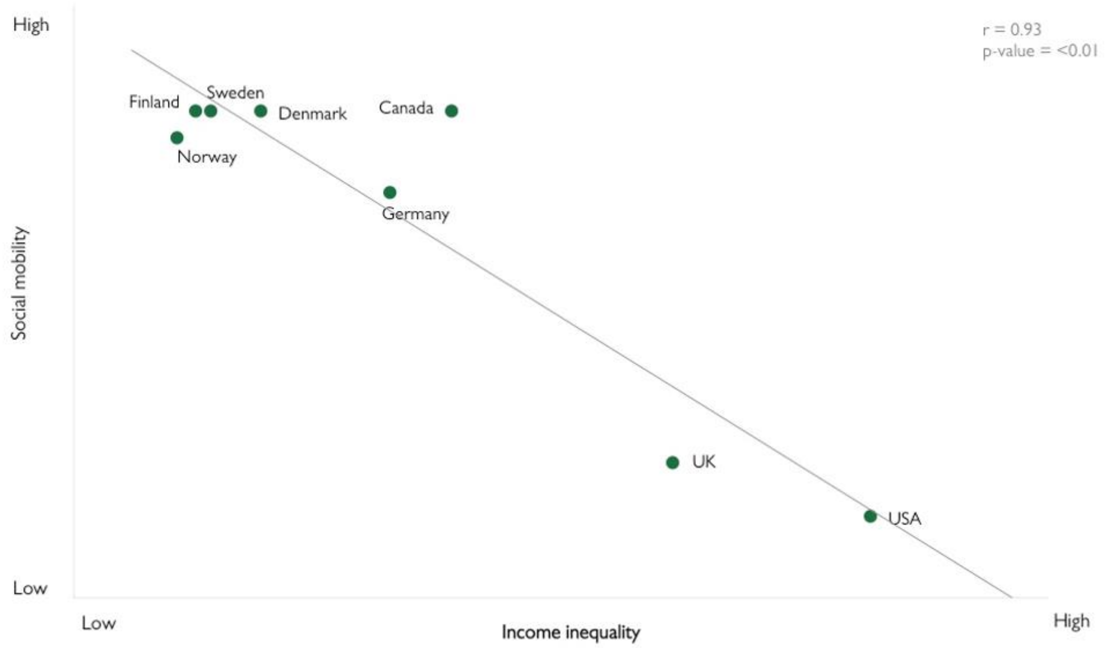

Figure 5. The relationship between income inequality and social mobility (Wilkinson and Pickett, 2010).

Furthermore, a relationship between income inequality and educational attainment is shown by Wilkinson and Pickett (2010). Figure 6 shows this relationship between income inequality and educational attainment. To determine the educational attainment, data which reveal the averages of math and literacy scores in 24 countries are used. These data come from the Program for International Student Assessment (PISA). PISA is a program with the aim to administer standardized tests to 15-year-olds in schools in different countries, with the goal to test how well children are able to apply knowledge and skills. The reason 15-year-olds are approached for this programs is because in most countries they are almost finishing compulsory education. Figure 6 reveals that more unequal countries have worse educational attainment. Wilkinson and Pickett show that these relationships are significant at a 96% confidence level.

Figure 6. The relationship between income inequality and the average of math and reading scores (Wilkinson and Pickett, 2010).

2.4.2. *Income Inequality and Social Capital*

This subsection elaborates on the relationship between inequality and the degree of social capital at a particular place. *Social capital* is described by Kawachi et al. (1997) as the features of social organization, such as civic participation, community life, social relations, norms of reciprocity, and trust in others. The presence of these features facilitates cooperation for mutual benefit. Kawachi et al. explain that social capital is a variable at the level of the *community* and is measured at the individual level by a person's social networks. Wilkinson and Pickett (2010) dedicated one chapter in their book on the relationship between income inequality and community and they claim that the quality of social relations deteriorates in less equal societies. They explain that inequality is a social *divider*, because people tend to consider differences in living standards as markers for differences in status. People have less to do with other kinds of people which makes it harder to trust them. A social hierarchy arises which affects who people see as part of their in-group and who people see as out-group. Wilkinson and Pickett claim that this affects people's ability to identify and emphasize with other people. This is in line with the findings of Elgar and Aitken (2011), who explain that one contextual indicator of social capital is interpersonal *trust* in a society. Whenever the income differences between people increase, the 'social distance' between these people increases as well. The authors mention that income inequality intensifies social hierarchies, which in turn affects the social anxiety and class conflicts. This erodes social trust and cohesion in a society. A similar finding has been done by Uslaner and Brown (2005), who claim that more inequality results in less trust and less caring for people who are different from oneself. When the level of trust is limited, people tend to act less kind to each other. Uslaner and Brown mention that the level of income inequality and trust predict the extent to which people are volunteering and giving charitable.

Several statements are made about the causal effect of income inequality on trust or the other way around. According to Putnam (2000) who wrote the book 'Bowling Alone' about the loss of social capital in the United States of America, the causal arrows of income inequality and decreasing social capital run in both directions. He states that people in an area with a high level of social capital are more likely to care about decreasing income inequality, and a high degree of income inequality is likely to be socially divisive. Bo Rothstein and Uslaner (2005), in Wilkinson and Pickett (2010) on the other hand, claim that inequality affects trust, but that there is no direct effect of trust on income inequality. They state that income inequality is the ‘prime mover’ of this relationship. The effect of income inequality on trust is reinforcing, according to Bo Rothstein and Uslaner. They state that high levels of income inequality leads to lower levels of trust, which will lessen the societal and political support to find resources to tackle these income differences.

Evidence of the relationship between income inequality and social capital is shown by Wilkinson and Pickett, using figure 5. Figure 5 shows the relationship between the income inequality on the horizontal axes and the percentages of people who agree with the statement “most people can be trusted” on the vertical axes, in 23 ‘developed’ countries. Wilkinson and Pickett used data from the European and World Values Survey in order to create this graph.

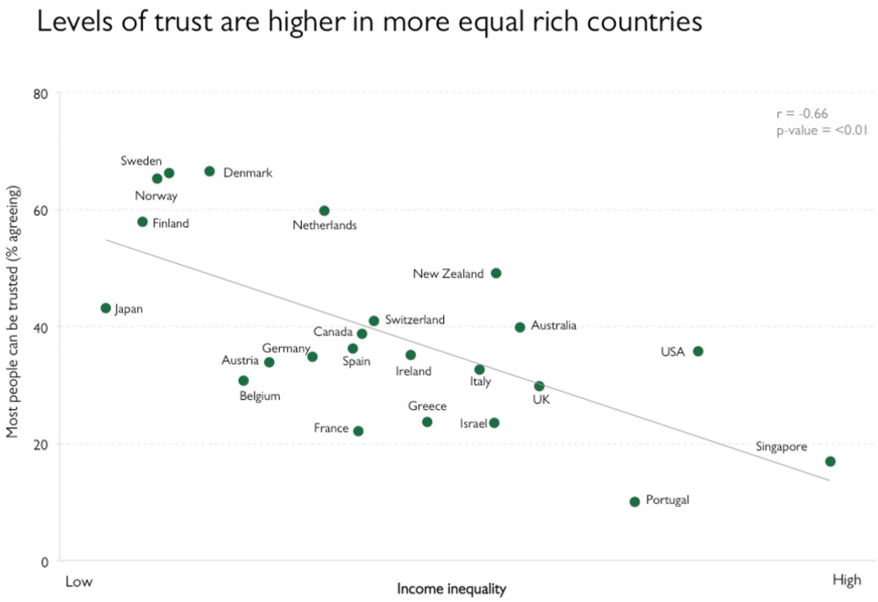

Figure 7. The relationship between income inequality and trust levels in 23 countries (Wilkinson and Pickett, 2010).

Wilkinson and Pickett demonstrate that the relationship shown in figure 5 is significant at a 99% significance level. The figure shows that the level of trust, based on the statement, is 6 times higher in the Scandinavian countries, where income inequality is relatively moderate, than in Portugal, where income inequality is relatively severe.

Another relation exists between social capital and health. Wilkinson and Pickett claim that people with higher levels of trust live longer. This relationship, and the relationship between income inequality and health is explained in more detail in the next subsection.

2.4.3. Income Inequality and Mental and Physical Health

A number of authors show the existence of a relationship between income inequality and the health levels in a region. Health can be distinguished into *mental* and *physical* health. Wilkinson and Pickett (2010) dedicate in their book a chapter to both these aspects of health. A strong association between income differences and health aspects come forward.

The authors explain that people who are mentally healthy are capable to look after themselves, see themselves as valuable people and judge themselves by reasonable standards. On the other hand, people who do not value themselves become frightened of rejection, according to Wilkinson and

Pickett. These people keep other people at a distance, and are trapped in a circle of loneliness. They explain that *status anxiety* is strongly present in an unequal society. Status anxiety is defined by De Botton (2004), in Wilkinson and Pickett (2010) as a worry to be capable of ruining extended stretches of our lives. When people fail to maintain their position in the social hierarchy, they tend to consider the successful people with bitterness and themselves with shame. People low on the income ladder experience the struggle to compete and keep up with the richer people. Low income status is associated with inferiority and stress, which produces negative emotions such as distrust and shame which have impact on the individual health through stress reactions. The status anxiety is, according to Layte (2012), mainly associated with unequal societies. These societies suffer more mental health problems as a result of the social anxiety.

Another important element is the influence of social capital, discussed in the previous subsection. Wilkinson and Pickett explain that in a society with high income differences, people are striving for material wealth and possessions, which results in loss of relationships, family life and quality of life. Social relations and trust are an important element of mental health. Layte (2012) states that more social trust is associated with 'collective efficacy', which means that neighbours and relative strangers are willing to offer social support or prevent abnormal behaviour. This will result in an increase in the overall level of quality of life. Therefore societies with low levels of community life and trust are also the societies with a relatively low level of mental health. Another explanation why income inequality results in health problems is provided by Kahn et al. (2000). They state that there might be a possibility that increased income inequality is negatively correlated with a society's investment in social goods such as accessible health care and public education.

Evidence of this relationship between income inequality and mental health is shown by Wilkinson and Pickett. Figure 6 shows a relationship between income differences and the proportion of adults who had been mentally ill in 12 'developed' countries. Wilkinson and Pickett used data of the World Health Organization in order to make the graph of figure 6. They show that the association between these two variables is significant at a 99% confidence level.

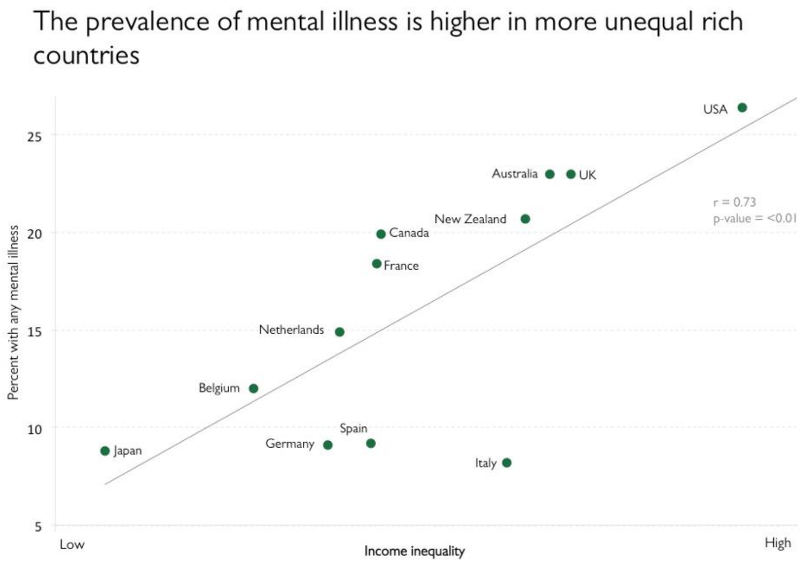

Figure 8. The relationship between income inequality and percent of people with mental illness levels in 12 countries (Wilkinson and Pickett, 2010).

In line with mental health is people's psychical health also affected by income inequality. Wilkinson and Pickett (2010) claim that income inequality is associated with physical health aspects, such as lower life expectancy, higher rates of infant mortality, shorter height, poor self-reported health and low birthweight. Evidence of the relationship is shown later in this subsection. This finding is in line with the insight provided by Kawachi and Kennedy (1999) who explain that income inequality is associated with higher rates of mortality, and also with higher rates of death from coronary heart disease, malignant neoplasms, homicide and infant mortality. In addition to this finding, Sturm and Gresenz (2002) found a significant correlation between self-reported health and inequality at the population level. Fiscella and Franks (2000) also found the existence of this relationship, however they did not find a relationship between income inequality and mortality.

Various authors indicate that through mental health, income inequality affects physical health. This is, for example, explained by Fiscella and Franks (2000), who mention that income inequality is associated with depressive symptoms, which then result in a lower self-reported health and higher mortality. The relationship between these variables is shown in figure 7. Although Fiscella and Franks have not been able to demonstrate the relationship between income inequality and health, this figure provides a good insight into how income inequality and physical health are related to each other.

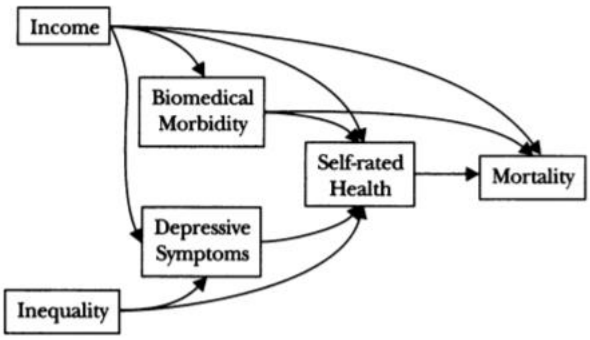

Figure 9. Pathways among a range of variables (Fiscella and Franks, 2000).

The association between income inequality and mortality, through mental health, is also underlined by Kawachi and Kennedy (1999). They state that income inequality is associated with disinvestment in human capital, erosion of social capital and social comparisons. These relationships are in line with the relationships between income inequality and mental health as described above. The association mentioned by Kawachi and Kennedy above is associated with stress, anxiety, frustration and limited possibilities. Wilkinson and Pickett (2010), who claim that income differences are associated with the physical health of people, describe the mechanisms that subsequently lead to reduced physical health. They mention that people with low job *status* are more vulnerable to cancer, chronic lung disease, gastrointestinal disease, depression, suicide, sickness absence from work, back pain and self-reported bad health. For an important part, this is caused because people in lower job grades are more likely to be obese, to smoke, to have higher blood pressure and to be less physically active. Another factor they mention is linked to the 'social capital' aspect which is underlined in subsection 2.4.2. Having strong relationships with other people and being integrated in society are all protective of health. But according to Wilkinson and Pickett, the most important factor is the job stress and the sense of control people have over their work, reinforced by the large differences between people from different socio-economic statuses. They claim that the psychological wellbeing of people has a direct impact on the physical health:

"The psyche affects the neural system and in turn the immune system – when we're stressed or depressed or feeling hostile, we are far more likely to develop a host of bodily ills, including heart disease, infections and more rapid ageing. Stress disrupts our body's balance, interferes with what

biologists call 'homeostatis' – the state we're in when everything is running smoothly and all our physiological processes are normal" (Wilkinson and Pickett, 2010 p. 85)

Wilkinson and Pickett believe a causal relationship exists between psychological well-being and the physical health level of an individual and based on the foregoing, they believe in a relationship between income inequality and physical health. When income is more evenly distributed among a society, the wealth of the whole society is better. The figures below give evidence of this relationship. Figure 8 shows the relationship between income inequality and life expectancy in 23 'developed' countries and figure 9 shows the relationship between income inequality and infant mortality in these countries.

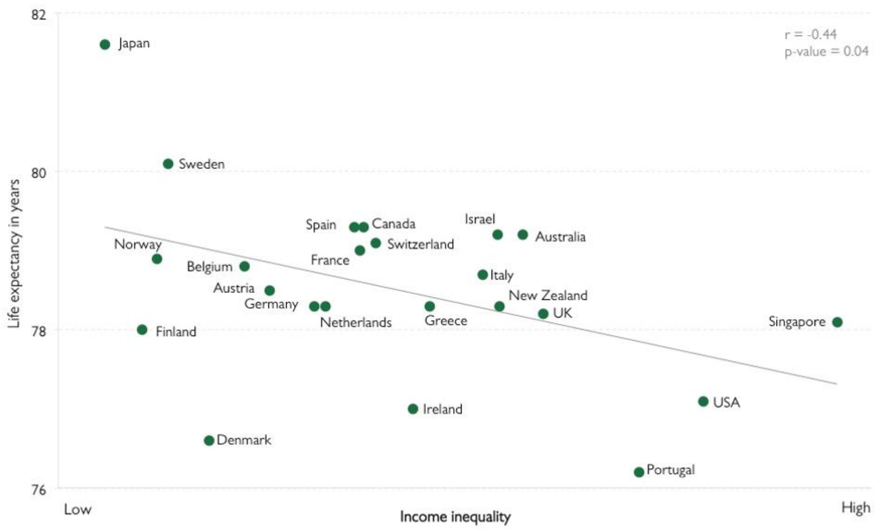

Figure 10. The relationship between income inequality and life expectancy in years in 23 countries (Wilkinson and Pickett, 2010).

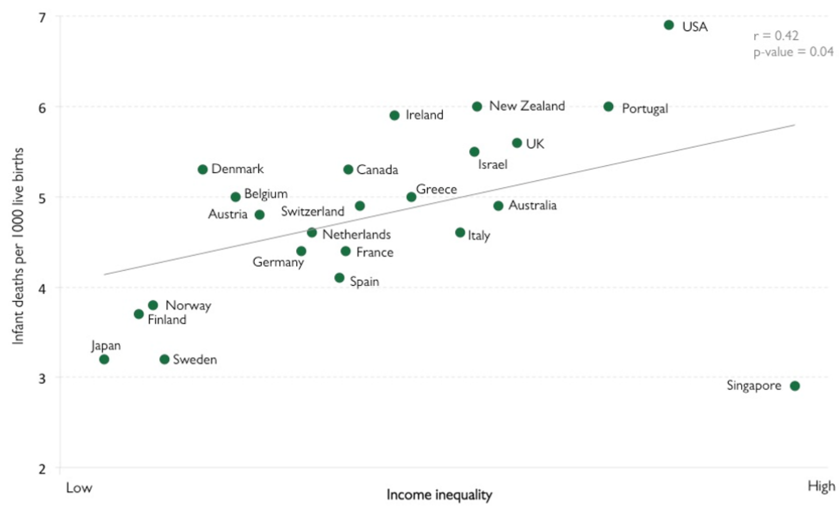

Figure 11. The relationship between income inequality and infant deaths per 1000 live births in 23 countries (Wilkinson and Pickett, 2010).

An important note made by Wilkinson and Pickett is that population averages, shown in the graphs above, do not show the differences in health *within* a society, which can be even stronger than the differences *between* countries. In addition to the above, Wilkinson and Pickett explain that deaths due to a heart attack and homicide had the largest class differences; they were considerable higher among the working class. In addition, deaths with large class differences were much more prone to inequality.

Another finding Wilkinson and Pickett did, is that living in a more equal place is better for *everybody,* not just for the poor. Health disparities run across society and benefits of equality improves health for everyone. According to the authors, living at a more equal place is better for people at almost any level of income. This phenomenon is called the *spillover effect* and is explained below.

2.5. Spillover Effect

A logical line of thought is that income inequality has a major impact on people who earn the least. However, it appears that income inequality also affects people from higher income classes. This phenomenon, which is also called the *spillover effect*, is elaborated on in this subsection. As it was also briefly discussed above, Kawachi and Kennedy (1997) argue that income inequality has a spillover effect on society at large, due to increased crime and violence, impeded productivity and economic growth and the impaired functioning of the representative democracy. They state that reducing income inequality will result in a greater social cohesiveness and better population health. The existence of a spillover effect, with regard to population health, is also explained by Lynch et al. (2004). They discussed a study in the British Medical Journal (1996) where it is claimed that the overall mortality rate is lower, and health is better in a society where wealth and income is evenly distributed. It is assumed that income inequality is a determinant of the population health of a particular society. Furthermore, this statement is in line with the outcomes of Kondo et al. (2009) who claim that income inequality is not only affecting the health of the poor, but the health of the whole society. Wilkinson and Pickett (2010) also agree with the existence of a spillover effect. According to them, groups of people with the same income do better in equal societies than in unequal societies. They describe that across *whole* populations, rates of mental illness are five times higher in the most unequal societies, compared to the least unequal societies. Even more so, they show that death rates, at all levels of income, were lower in more equal American states than in more unequal American states.

There are various mechanisms that clarify the spillover effect. Kawachi and Kennedy (1997) discuss some of these mechanisms that cause the spillover effect. They state that wide income differences result in first instance in frustration, stress and family disruption, which then increase the level of crime, violence and homicide. Antisocial behavior and limited access to facilities increase in places with a high level of income inequality, which affects, according to Daly et al. (1998), the whole population. Kawachi and Kennedy describe that people who can afford make the decision to move to gated communities or similar living arrangements. This *middle class flight*, as the authors name it, leads to deterioration of the public education systems and erosion of support for public schools. An underclass of poorly educated and underskilled people is arising, which results in slower economic growth and lower productivity, which the entire society will have to pay for.

Another mechanism that causes a spillover effect can be observed in the realm of social capital, which is discussed in subsection 2.4.2. Kawachi and Kennedy refer to the work of Robert Putnam (2000) to describe this mechanism. As described in subsection 2.4.2., a large degree of income inequality leads to declining civic trust, which according to Putnam also leads to less political trust and confidence. People living in a place where income differences are limited, experience their social environment as less hostile and more hospitable. This phenomenon does not only relate to lower incomes, but people higher up on the income ladder experience less trust in others. Wilkinson (1997) indicates that there is a positive link between cohesion and population health. He explains that the social environment is crucial for people's psychological welfare and the prevalence of chronic stress in a population. The above supports the idea of the existence of a spillover effect. It is assumed that income inequality leads to less cohesion in a society, which can lead to increasing stress and frustration resulting in decreasing physical and mental health.

A third mechanism is related to *status*, which is also explained in paragraph 2.4.3. Income inequality results in increasing social comparisons and status anxiety. According to Kondo et al. (2009), this social comparison leads to psychological stress and has consequences for the entire society, consisting of people from different income groups. However, one may wonder whether this mechanism leads to a spillover effect. However, Subramanian and Kawachi (2006) assume that social comparisons are only harmful to the poor and advantageous for people with higher incomes, due to their status. This shows that there are different views, from different authors, on whether this mechanism results in a spillover-effect.

In short, various authors indicate that there is a spillover effect. This means that not only the lower income classes experience negative outcomes due to income inequality, but also people with higher incomes do so. Various mechanisms, as described above, explain this phenomenon. The existence of a spillover effect implies that equal incomes are advantageous for the whole society.

2.6. Income Inequality and Institutions

What has been described above would be useless if there were no means to act upon income inequality. That is why this subsection deals with ways in which institutions can influence income inequality. An institution is an entity that is broadly conceived. Helmke and Levitsky (2004) describe 'institutions' as *rules and procedures (both formal and informal) that structure social interaction by constraining and enabling actors' behavior* (Helmke and Levitsky, 2004). These rules and procedures can be imposed by governments, organizations, social networks and so on. Checchi and García-Peñalosa (2008) argue that *labour market institutions* have influence on the degree of income inequality in an economy. Examples of labour market institutions, provided by Checchi and García-Peñalosa, are the coverage and density of unions, the coordination and centralization of wage bargaining, existence and level of minimum income, unemployment benefits, employment protection legislation, tax wedges, and active labour policy. The authors show by means of correlations that labour market institutions have a significant impact on the distribution of income. Stronger institutions are correlated with lower inequality measured in Gini-coefficient. Checchi and García-Peñalosa explain that institutions have the ability to decrease wage dispersion. Two elements of institutions are, according to them, relevant to do this. Institutions have the ability to set wages, as a result of which the market cannot run free. This guarantees people a certain wage, and too large differences between wages are made impossible. Besides, there is the element of employment security which indicates job security and out-of-job income. Wilkinson and Pickett (2010) also link the arise of income inequality to institutions. They claim that changes in inequality are driven by "changes in institutions, norms and political power". Reasons for increasing income inequality, according to them, are the weakening of trade unions, the abandonment of productivity sharing agreements, changes in taxes and benefits, and the failure to maintain adequate minimum wage legislation. De Mello (2006) also focussed on institutions and conducted research on the influence of redistributive public spending on inequality and found out that countries where redistributive public spending is most needed, which are countries with low per capita income and high inequality, are less likely to redistribute income through public policies. De Mello notes that this is linked to the "incomplete markets" view of the association between inequality and redistribution, where inequality is perpetuated over time when a share of the people, mainly the poor, have limited access to capital markets to insure themselves against economic shocks or to make investments which are necessary to improve their future earnings capacity. De Mello concludes that emphasis on government spending to tackle income inequality depends on the country's inequality level. He adds to this that redistributive policy may be inefficient because the benefits of public spending may be captured by the non-poor.

The institutions and their redistributive policy described above have a direct influence on income inequality. However, other aspects can also be considered which have a more indirect influence on income inequality. Even more so, evidence shows that actions of institutions do not explain the whole story. Wilkinson and Pickett explain that Japan, the country with the lowest level of income inequality in their research, manages to achieve low levels of income inequality *before* taxes and benefits: differences in gross earnings in Japan are smaller. Several authors put emphasis on the degree of democracy in a society and firms and organization within this society. Reuveny and Li (2003) mention that democracy affects the distribution of income through the process of competing pressures. They state that the government is subject to pressure from interest groups. A higher degree of democracy gives rise to labour unions and political parties and organizations that represent the lower and middle classes. When these organizations are vital and organized, they have the ability to influence policy making. Reuveny and Li refer to Lenski (1966), who claims that democracy redistributes political power in favour of the majority and therefore leads to policies that reduce income inequality. Even more so, they mention that democracy increases the opportunities for participation and allows the poor to demand more equitable income distribution. They claim that democratic governments are more inclined to help the lower and middle classes. Wilkinson and Pickett (2010) also put emphasis on involvement of interactions and involvement of citizens. They consider democracy from the perspective of a firm and discuss *democratic employee-ownership* in which ownership of the firms is shared by employers and employees and participative management methods are used. Wilkinson and Pickett claim that shared ownership improves company performance and production by reducing the opposition of interests between employers and employees, and people have a higher level of control and autonomy and feel they are part of a community. The authors explain that *employee-ownership* has the ability to increase equality. They claim that large differences between employers and employees can only be maintained when there is a lack of any form of democracy. The scale of earning differentials are put under democratic control and people are freer of hierarchal divisions. It should be considered that, even when employee-ownership exists, making profit remains the main objective of a company and can still lead companies to act in anti-social ways to earn a higher profit. Besides, it is doubtful if employees want to have more responsibilities next to their tasks. (Wilkinson and Pickett, 2010). Still, employee-ownership offers an interesting framework for tackling income inequality at the firm-level. In a bigger context, Wilkinson and Pickett are convinced that income differences are subject to democratic control and that greater equality is deeply rooted in the *social fabric*.

2.7. Other predictors of well-being and health

All the above is related to the concept of income inequality. However, there are also many other predictors of well-being and health. During the empirical analyses of this research, several other predictors of well-being and health are also taken into account. This is done in order to create a more complete story of the impact income inequality has on well-being and mental and physical health. Oswald and Wu (2009) conducted research to get insight in the predictors of well-being in the United States. For this research they used data provided by the BRFSS from 2005 to 2008. Variables they used, in order to get insight in well-being are: *life satisfaction* and *mental distress*. By conducting regression analyses, their research shows that these two variables have a significant relationship with the income levels of people, the age of an individual, the marital status of a person, the state where someone is living, the employment state of someone and the educational level of someone. The research of Wu and Oswald shows that older people have a lower level of life satisfaction and lower self-assessed mental health. The same goes for individuals with higher incomes. Besides, it is shown by Oswald and Wu that people who graduated high school or college have a higher level of life satisfaction and a higher self-assessed health than people who did not graduate. The same finding turns out for married people in contrast to people who are single. Furthermore, people who are unemployed have a lower level of self-assessed health and life satisfaction than people who are employed, self-employed or people who are homemakers. Looking at American States, Oswald and Wu used Alabama as reference category. The first model Oswald and Wu executed only consists of the American states as predictors of mental well-being and life satisfaction. In this model it turns out that Wyoming, Minnesota, Louisiana, Hawaii, Colorado and Utah have the highest level of life satisfaction, compared to Alabama. From the perspective of Alabama, the lowest level of life satisfaction can, according to the model used by Oswald and Wu, be found in West Virginia, Pennsylvania, Missouri, Indiana and Kentucky. Considering the self-assessed mental health, it turns out that, comparing to Alabama, Iowa, Kansas, Louisiana, Nebraska and both Dakota's have the highest level of self-assessed health. The model shows that there is not any single state where the level of self-assessed health is significantly lower than in Alabama. However, in the states of Utah, Oklahoma, Ohio, Missouri, Mississippi, Michigan and Indiana, the level of self-assessed health is significantly different from Alabama and these states have the lowest negative coefficients of all states which are significantly different from Alabama.

A similar research was conducted by Staudinger et al. (1999), by making a comparison between Germany and the United States. They found out that in the United States, the social economic status of someone is a relatively strong predictor of the subjective well-being of an individual. Furthermore they found that *self-regulatory indicators* are strong predictors of well-being in both countries. They state that self-regulatory indicators are considered as building elements of effective functioning. An indicator they used for this was *psychological control,* which is the level of control people have in life domains such as work and health. This finding is supported by Lachman and Weaver (1998) who found out that a high level of 'mastery' and low perceived constraints result in higher levels of life satisfaction and health. A second indicator Staudinger et al. used is the *personal live investment*, which is linked to the level of investment that people put in these same life domains. Other significant predictors of mental health and well-being they found, are age and gender of someone. However, these two predictors show a weak relationship with well-being and mental health. Other predictors of well-being and mental health they found are linked to the personality of an individual. Another similar research is conducted by Ryff (1989) who used a number of different dependent variables to get insight in well-being. Some of these variables are: self-acceptance, depression, and life satisfaction. He found relations between the variables and self-rated health, finances, marital status, age, and educational attainment. Other research to the self-reported happiness was conducted by Luttmer (2004) who found a wide range of factors significantly influencing this self-reported happiness. Some of these factors are: household income, being a renter, house value, work status, age, satisfaction with family life, satisfaction with financial situation, satisfaction with home and satisfaction with social life. Another predictor that has a substantive impact on well-being is *poverty.* Diener and Biswas-Diener (2001) indicate that poverty can and does lower the level of subjective well-being. The findings of Haushofer and Fehr (2014) are in line with this. They mention that poverty results in stress and negative affective states. The authors mention that people in poverty have the feeling that they lose control and make short-sighted and risk averse decisions. This mechanism results in lower levels of mental health and higher levels of depressions, unhappiness, anxiety and cortisol level. A last point of interest is the influence of housing on well-being. An Australian research is conducted by Robinson and Adams (2008). They wrote an article about the impact of house prices and rent prices on mental health and well-being. They state that, since housing is a basic need for all humans, higher housing costs and house prices may result in ‘housing stress’, which again has impact on the mental well-being of an individual. This conclusion is in line with the findings of Rowley et al. (2015), who also conducted research to the concept of ‘housing stress’. They claim that housing affordability is linked to household financial outcomes where high housing costs relative to income are perceived to negatively affect well-being. Considering this argumentation, rent has impact on the financial situation of an individual which in turn influences the well-being of that person.

2.8. Conceptual Framework

The figure below shows the most important relationships between factors that are discussed in the theoretical framework and the mechanisms that lead to these relationships. A '+' in the model means that there is an increase in the value of a particular variable, and a '-' means that there is a decrease in the value of a particular value. This framework forms the basis for the further empirical research.

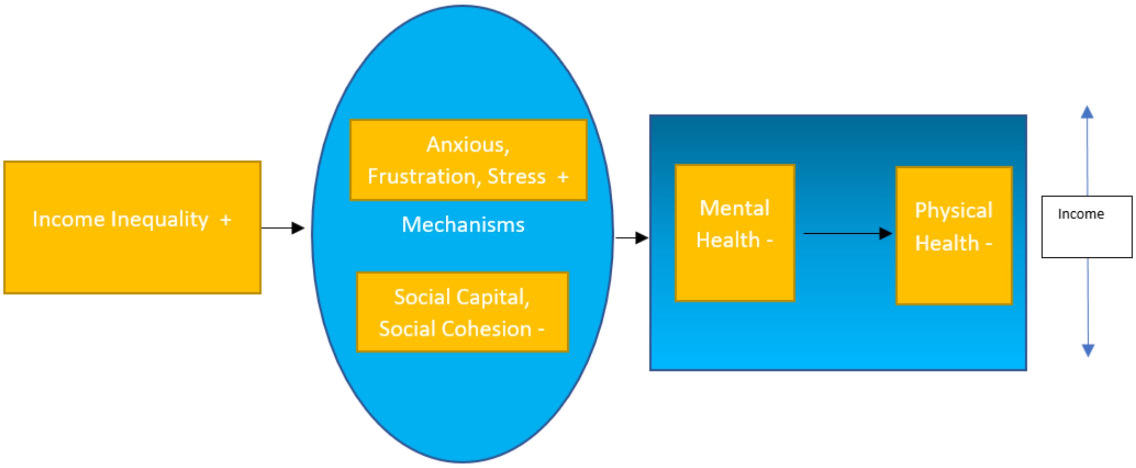

Figure 12. Conceptual framework with important findings from the theoretical framework.

2.9. Summary of Discussed Literature

Income inequality is described as the income distribution expressible as a function of inequality *between* nations or societies and inequality *within* nations or societies (Cowell and Jenkins (1995). Measuring income inequality could be applied on different geographical scales which may involve inequality within and between constituent subgroups of the population of a particular country. There exist different ways to measure income distribution and inequality. For this research, there is chosen to use the Gini-coefficient as measure. A Gini-coefficient of 0 represents a society in which the income is perfectly equally distributed. On the other hand, a Gini-coefficient of 1 represents a society wherein all income is earned by one single person (De Maio, 2007).

Income inequality is linked to the social and geographical context of an individual, and this context is associated with a wide range of factors (Ballas, 2013). People compare their own situation with other people in their social and geographical context. Therefore, income inequality affects the quality of life and well-being at a particular place. Income inequality has influence on health due to perceptions of place in the social hierarchy based on relative position of income.

Consequences of large income differences between people are mentioned by Thorbecke and Charumilind (2002), Wilkinson and Pickett (2010), Lynch et al. (2000) and Kawachi and Kennedy (1997) who state that income inequality affects (mental) health education performance, teenage births, homicides, imprisonment rates, social mobility, obesity, life expectancy, infant mortality, political and social conflicts, crime, social cohesion and trust between people in cities and neighborhoods.

This research focuses in particular on the effects of income inequality on mental and physical health. In a nutshell, it comes forward that a higher level of income inequality results in *more status anxiety, lower levels of trust, less social capital, less social cohesion* and *more class conflicts,* which results in higher levels of stress, frustration and lower levels of mental health, which in turn results in lower levels of physical health. Wilkinson and Pickett (2010), Kawachi and Kennedy (1999) and Sturm and Gresenz (2002) found evidence that a negative relationship between income inequality and mental health levels exists. Wilkinson and Pickett show in their book "*The Spirit Level – Why Equality is Better for Everyone*" (2010) that when income inequality in a country or state is higher, the mental health level is lower in this country or state: there are more people with mental illnesses. Evidence for a similar relationship between income inequality and physical has been found by Wilkinson and Pickett (2010), Kawachi and Kennedy (1999), Sturm and Gresenz (2002), and Fiscella and Franks (2000) who showed that the level of income inequality is negatively affecting physical health levels. However, evidence is mainly found at higher geographical scale levels, such as countries and American states. At lower geographical levels, the relationships between income inequality and health are not taken into account, while at lower geographical scales, mechanisms related to social cohesion, social capital, trust etc. may play a very important role. Therefore, in the research presented here, analyses are also conducted at the lower geographical scale levels, such as counties and cities.

Various authors indicate that there exists a *spillover effect* on society at large. This means that not only the lower income groups experience negative outcomes due to income inequality, but also people with higher incomes. The existence of a spillover effect implies that equal incomes are advantageous for the whole society. Several authors, such as Lynch et al. (2004), Kondo et al. (2009) and Wilkinson and Pickett (2010) claim that income inequality affects the population as a whole. However, it is not shown that income inequality really affects people with higher incomes. This research focuses on the influence of income inequality on mental and physical health levels, across different income levels. This kind of analysis provides an indication as to what extent people with higher incomes are affected by the level of income inequality.

The contextual effect of income inequality, where lower geographical levels are taken into account, and the so-called *spillover effect,* which focuses on the impact of income inequality across higher income groups, have been examined to a limited extent in the existing scientific articles. This research attempts to provide insight in these aspects of income inequality.

3. Methodology

The methodology of this research is explained in this section. The first subsection explains the study area this research is focussed on. The focus of this research is mainly on the scale level of Orange County, California and the United States. Then, the second subsection elaborates on the data which are used in order to carry out the analyses. Three different data sources are used. The last subsection elaborates on the methods which are used in order to carry out the analyses. Different statistical methods have been used to carry out this research.

3.1. Study Area

This research has been conducted at multiple scale levels. The lowest scale level this study takes place, is the Census Tract level. Census Tracts are small, relatively permanent statistical subdivision of a county or equivalent entity (US Census Bureau, 2018). At the website of the US Census Bureau is described that Census Tracts generally have a population size between 1200 and 8000 people, with an optimum of 4000 people. A Census Tract usually covers a contiguous area, but the spatial size of Census Tract vary depending on the density of settlement.

As mentioned, the focus of this thesis is partly on Orange County in this thesis. The reason that there is focused on this particular county is because this study is done in cooperation with the University of California, Irvine (UCI). Irvine is located in Orange County. A second reason to focus on Orange County is because it stands out that in this county the level of income inequality is high in comparison with California and the United States. This is demonstrated in the introduction of this thesis. Furthermore, there is focused on higher scale levels, which are the level of California and the level of the United States. In this research, comparisons are done *within* and *between* the patterns of different scale levels. The way this has been carried out, is explained further in this section.

Figure 13. Location of Orange County (World Atlas, 2018).

3.2. Data

As mentioned in the introduction of this thesis, the objective of this research is to find out to what extent the so-called spillover effect exists. The spillover effect presumes that income inequality has a socio-economic and psychosocial impact on the society at large, which means that income inequality also has impact on people with higher incomes (Kawachi and Kennedy, 2007). Related to this main objective, another aim of this research is getting insight in the extent to which income inequality has impact on socio-economic and psychosocial factors. This impact is related to the different geographical scale levels and the existing income inequality at these different scale levels. Comparisons are done *within* and *between* the different geographical scale levels.

3.2.1. U.S. Census – Local Area Data

To get insight into the impact of income inequality and *the spillover effect*, three different data sources have been used. A first data source that is used, is information from the U.S. Census Bureau. The Gini-coefficients, which show the level of income inequality, (see subsection 2.2.1.) of cities, counties, states and the United States are available at the American Factfinder, which is a platform of the U.S. Census bureau with information about a wide range of topics at the state-, county-, city-, town-, or zip code level (U.S Census Bureau, 2018). Data about income inequality and other information at different scale levels are used for explanatory reasons and as independent variables for several analyses. Data provided by the U.S. Census, which are used in this research, are *Gini Coefficient* at the *Census Tract level, median income, work force ratio, unemployment, rate of people below the poverty line, median gross house rent, rate of people who graduated high school* and the *Gini Coefficient* at the level of the *city* (for the analysis at the County-level), *county* (for the analysis at the state-level) and *state* (for the analysis at the country-level). These collected data are averages of Census Tracts.

3.2.2. 500 Cities Project

Another data source that is used in order to conduct this research, is the 500 Cities Project, which is a collaboration between CDC, the Robert Wood Johnson Foundation, and the CDC Foundation (CDC, 2018). The aim of the 500 Cities Project is to get insight in the health patterns across the 500 largest cities in the United States. The 500 Cities Project provides health-related data at the Census Tract level, which means that the data are averages of Census Tracts. The most recent dataset of the 500 Cities Project from 2016 is used. From the 500 Cities Project, two variables are used in order to conduct this research. Both variables are used as dependent variables. The first variable that is used, is "*MHLTH_CrudePrev*", which shows the percentage of respondents, 18 years and older, who report 14 or more days during the past 30 days during which their mental health was not good (CDC, 2018). A second variable that is used, is "*PHLTH_CrudePrev*", which shows the percentage of respondents, 18 years and older, who report 14 or more days during the past 30 days during which their physical health was not good (CDC, 2018). As mentioned, these data are collected at the Census Tract level, and also the cities and states where the Census-Tracts are located, are variables in this dataset. Based on the cities and states which are variables of this dataset, the county where the Census Tract is located, is added as a variable. From the dataset of the 500 cities project, three different datasets are created, of which the highest geographical scale levels are respectively: the *United States*, *California* and *Orange County*. The reason these three datasets are created, is because it provides the opportunity to make comparisons *between* and *within* different geographical scale level which is explained in subsection 3.3.2.

3.2.3. The Behavioral Risk Factor Surveillance System *(BRFSS) data*

A last dataset that is used to conduct this research, is the *Behavioral Risk Factor Surveillance System* (BRFSS) from 2016. The BRFSS is an American survey which collects data about U.S. citizens with regards to their health-related risk behaviors, chronic health conditions, and use of preventive services. The lowest geographical information scale information that is provided in this dataset is the state a respondent is living. The reason to choose this dataset in order to conduct the analyses for this research is explained in subsection 3.3.3. A number of variables from this dataset is used.

Two dependent variables from this dataset are: *Number of Days Mental Health Not Good* and *Number of Days Physical Health Not Good*. These questions are based on the month before the respondent completed the survey.

The two dependent variables are determined by the questions: *"Thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"* and *"Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your physical health not good?".* Respondents had to report an integer between zero and 30.

A number of independent variables are used for this research: income, age, state, sex, education and employment. The influences of these variables on health and well-being are discussed in section 2.7.

A first independent variable that is used for the analysis is *income*. Eight different income groups on an annual basis are used. Respondents had to indicate which income group they were part of, based on their annual income. Income is, by the BRFSS, grouped in eight different categories, which are: *less than $10.000* (=1), *between $10.000 and $14.999* (=2), *between $15,000 and $19.999* (=3), *between $20,000 than $24.999* (=4), *between $25,000 and $34.999* (=5), *between $35,000 and $49.999* (=6), *between $50,000 and $74.999* (=7) and *more than $75,000* (=8). These income distributions have been used in various studies for various purposes. Examples of authors who used the income distribution as above in order to conduct an analysis, are Kwon et al. (2011), Philip-Salimi et al. (2012) and Volland (2012). Abeyta et al. (2012) stratified these income groups, in three categories and labeled the three categories with an annual income lower than 25,000 as *Low Socio-Economic Status*, the categories with an annual income between 25,000 and 50,000 were labelled as *Middle Socio-Economic Status* and incomes higher than 50,000 were labeled as *High Socio-Economic Status*. In this research, all eight income groups are used for the analyses. These eight income categories give the possibility to get insight in the spillover effect by making comparisons between different income categories across different socio-economic statuses, with regards to the influence of income inequality on mental and physical health levels.

The variable *age* is represented by 13 groups with a range of 5 years. The lowest age group is 18-24 and the highest age group is 80 years and older. Another dependent variable that is used, is the *state* where a respondent is from. All 50 American states are included in the dataset. Furthermore is the *sex* of the respondent is taken into account and whether the respondent is married or not.

Two other independent variables which are taken into account, are *education* and *employment. Education* is represented by six different groups: "*Never attended school or only kindergarten*" (=1), "*Grades 1 through 8 (Elementary)"* (=2), "*Grades 9 through 11 (Some high school)"* (=3), "*Grade 12 or GED (High school graduate)"* (=4), "*College 1 year to 3 years (Some college or technical school)"* (=5), "*College 4 years or more (College graduate)"* (=6).

The variable *employment* is represented by eight different groups: "*Employed for wages*" (=1), "*Self-employed*" (=2), "*Out of work for 1 year or more*" (=3), "*Out of work for less than 1 year*" (=4), "*A homemaker*" (=5), "*A student*" (=6), "*Retired*"(=7), "*Unable to work*" (=8).

For each variable in the survey, respondents could choose not to answer the question.

3.3. Methods

As mentioned above, three different sources are used in order to obtain the data which are relevant to conduct this research. The ways in which these data are analyzed, are explained in this section. Besides, the value and the reasons for these methods are discussed.

3.3.1. Measuring Income Inequality

Firstly, an overview is provided of the levels of income inequality in the areas which are analyzed. This creates a basis framework for the remainder of the research and provides an answer to the second sub question: *What are the socio-economic and psychosocial consequences of income inequality in the context of Orange County, California and the United States?* Since the Gini-coefficient is the most common way to measure income inequality and because it is relatively easily interpretable and comparable, as explained in section 2.2.1., there is chosen to use this measure during this research. An explanation of the way to use and interpret the Gini-coefficient is given in paragraph 2.1.1. This analysis occurs at different scale levels. The highest scale level is the U.S.-level and the lowest level is the census-tract level. This research focuses in particular on Orange County, California and the United States. Therefore, the Gini-coefficient of the cities in Orange County, the counties in California and the states in the U.S. are taken into account. The different Gini-coefficients are shown in a table and are mapped. This overview is a basis framework for the remaining of the analysis.

3.3.2. Multilevel Analysis: Explaining The Contextual Effect of Income Inequality

One of the secondary questions of this research is: "*To what extent are the social-economic and psychological consequences of income inequality related to their geographical context*?". The aim of this question is to find out to what extent a relation exists between social-economic and psychological indicators, and income inequality at different geographical levels. To answer this question, a multilevel analysis has been carried out. The basic demand for a multilevel analysis is that the dataset is a *multistage sample* and that it consists of *clusters.* The dataset should have a multilevel data structure which means that they constitute hierarchically nested systems with multiple levels (Snijders & Bosker, 1999). Ballas and Tranmer (2012) conducted a multilevel analysis in order to get insight in the regional perspective and geographical component of self-reported happiness and well-being. They mention that multilevel models can address issues of spatial dependence and heterogeneity. A key advantage of conducting a multilevel analysis, according to Ballas and Tranmer, is that the estimated coefficients, and their standard errors, take into account clustering at various geographical levels of the population structure, which makes it less likely that coefficients are biased due to population structure and grouping. Furthermore, Ballas and Tranmer mention that an important advantage of multilevel modelling is that it is possible to estimate different intercepts for various geographical and group levels, and it can be measured how these intercepts may be affected by adding explanatory and control variables.

The dataset provided by the *500 cities project* consists of different scale levels. The units in the dataset are at the *Census Tract level:* this is an aggregate of people living in a particular Census Tract. Values in the dataset concern averages of these Census Tracts. These Census Tracts are parts of *cities*. The focus with regard to cities during this analysis is on cities in Orange County. Furthermore, during the multilevel analysis *counties* are taken into account. With regard to counties, there is chosen to focus on counties in California. A last scale level of this research is the *state* level. This involves focusing on all states of the U.S.

By conducting a multilevel analysis, insight can be obtained into the extent to which a relationship exists between social-economic and psychological indicators, and income inequality and a number of predictors, at different geographical levels. A multilevel analysis provides the opportunity to analyze the relation between and within groups, such as cities, counties or states. The dataset contains information about the city, county and state, so it could be claimed that the dataset has a multilevel data structure. In the case a dataset has a multilevel proposition, the researcher might be interested in the effect of a macro-level variable on the micro-level variable (Snijders & Bosker, 1999). With regards to the 500 cities project-dataset, it is interesting to analyze the city-, county-, or state-effect on the Census Tract averages. This might reveal to which extent a city-, county- or state-effect exists with regards to the relation between social-economic and psychological indicators, income inequality and several other predictors. The indicators which are included in the 500 cities project-dataset concern *mental health* and *physical health*. Three different datasets are created from the 500 cities project-dataset. Orange County is the highest geographical level of the first dataset, and this dataset is used to analyze the city-effect in the relationship between mental and physical health and a number of predictors with the emphatic focus on income inequality. In addition to this, California is the highest geographical level of the second dataset, and this dataset is used to get insight in the county-effect in the relationship between mental and physical health and a number of predictors where the focus is mainly on income inequality. The last dataset includes the whole U.S. and is used to analyze the state-effect in the relationship between mental and physical health, and a number of predictors where there is mainly concentrated on income inequality. In short, a multilevel analysis reveals the effect of a macro-level variable, in this case a city, county or state, on a micro-level variable, in this case the average of a Census Tract.

In their book about multilevel modelling, Snijders and Bosker (1999) explain how a multilevel analysis can be conducted. They elaborate on the *hierarchical linear model*. Short et al. (2005) provide an explanation of this hierarchical linear model (HLM). They mention that HLM provides a tool to conceptualize and test cross-level relationships where the dependent variable is at the individual level of analysis, in the case of this research, at the Census Tract average-level. For this research, HLM provides the opportunity to model cross-level relationships by specifying distinct level-1 (i.e., lower level observations, in the case of this study, the Census Tract-averages) and level-2 (i.e., higher level observations, in the case of this study, the cities, counties and states) models. Short et al. explain that the model is analogous to OLS regression. This study focuses on the health levels at micro-level (Census Tract average) explained by the Gini coefficient-variable at both the micro-level (Census Tract average), as the macro-level (city, county or state). Croon and Van Veldhoven (2007) describe explaining a phenomenon at the micro-level, by effects at the macro-level, as a *micro-macro multilevel situation*.

Three HLM-analyses have been carried out for each of the three datasets: the dataset with country, state and county as highest geographical scale level. Besides, different analyses have been conducted for mental health as dependent variable, as well for physical health as dependent variable. The distinction between analyses has been made, because it provides an indication as to whether the geographical context, the Gini-coefficient or both matter. The software programme Stata is used to conduct these analyses.

The first analysis only focuses on the relation between mental and physical health, and a number of predictors which are: *Gini Coefficient* at the *Census Tract level, median income, work force ratio, unemployment, rate of people below the poverty line, median gross house rent, rate of people who graduated high school* and the *Gini Coefficient* at the level of the *city* (for the analysis at the county-level), *county* (for the analysis at the state-level) and *state* (for the analysis at the country-level). This model consists of an OLS regression to get insight in the relationship between mental and physical health, and income inequality. This regression leaves the geographical context out of consideration and only considers the relationship between the Gini-coefficient and mental and physical health. The following equation indicates this model:

$$Yij = \beta 0ij + \beta_{ginicensustract} Xij + \beta_{medianincome} Xij + \beta_{workforceratio} Xij + \beta_{unemployment} Xij + \beta_{Poverty} Xij + \beta_{medianrent} Xij + \beta_{highschool} Xij + \beta_{Ginimacrolevel} Xij + Rij \tag{3.1}$$

In this model, *Yij* is the mental or health level as average of the Census Tract, *i* represents the Census Tract-average, which is an element of *j*, which represents the city, county or state. *β0* is the intercept and *β* stands for the coefficient of the different predictors. The residual or error term is represented by *R*.

In the following OLS regression, the independent variables have been left out of consideration. The focus in this regression is on the geographical context. An HLM-model without predictor variables is called a 'null model' (Short et al. 2005). The following equation indicates this model:

$$Yij = \beta 0j + Rij \tag{3.2}$$

The last OLS regression takes into account both for the geographical context, as for the different predictors:

$$Yij = \beta 0j + \beta_{ginicensustract}\, j\, Xij + \beta_{medianincome}\, j\, Xij + \beta_{workforceratio}\, j\, Xij + \beta_{unemployment}\, j\, Xij + \beta_{Poverty}\, j\, Xij + \beta_{medianrent}\, j\, Xij + \beta_{highschool}\, j\, Xij + \beta_{Ginimacrolevel}\, j\, Xij + Rij \tag{3.3}$$

The last two models could be considered as the aggregation of diverse separate regressions for each group *j*, which results in an outcome as average of the Census Tract: *Yij*. To get insight in the effect of the geographical context, it is interesting to measure the intraclass correlation in the dependent variables which is accounted for by aggregate level (Census Tract-average) and group level (city, county or state) effects. In order to do this, it is relevant to know the random effect (residual or error term) at the group level; *U0j*, and the random effect at the Census Tract-level; *Rij*. This is relevant because it provides the basic partition of the intraclass correlation (Snijders and Bosker, 1999). The total variance of Y can be decomposed as the sum of the variances of both levels:

$$var(Yij) = var\,(U0j) + var\,(Rij) \tag{3.4}$$

To get insight in the variance explained by the group structure, the intraclass correlation (ICC) is calculated.

$$p = var(U0j) \,/\, var\,(Yij) \tag{3.5}$$

This ratio provides insight in the percentage of intraclass correlation, which reveals in the amount of variance explained by group-level effects. The calculation of the intraclass correlation has been carried out for all models where geographical context is taken into account.

In short, the intraclass correlation provides insight in the extent to which the dependent variable (health rate) is influenced by the geographical (city, county or state) or Census Tract- (aggregate of individuals) context where the predictors are included as an independent variable in model 3.3. The intraclass correlation of model 3.3. gives insight in the extent to which different geographical contexts are of importance for the relationship between income inequality together with the other predictors, and mental and physical health. This gives insight in the last sub question of this research: *To what extent are the social-economic and psychological consequences of income inequality related to their geographical context?*

3.3.3. State Level Analysis: Looking for a Spillover Effect

The main question of this research is: *"To what extent does a spillover effect, caused by income inequality, exist in the United States?".* A spillover effect means that not only the lower incomes experience negative outcomes due to income inequality, but also people with higher incomes. Various mechanisms, as described in paragraph 2.5, explain this phenomenon. To get insight in the spillover effect, a dataset from 2016 by the *Behavioral Risk Factor Surveillance System* (BRFSS) has been used. The dependent and independent variables which are included in this dataset are mentioned in section 3.2. In addition to the existing variables, another variable has been added: the Gini-coefficient of 2016. This information has been obtained from the US Census Tract. Several regressions have been conducted to get insight in the relationships between the independent and dependent variables. In contrast to the 500 Cities-project, which has been used for the multilevel analysis, the micro-units of the BRFSS-datasets consist of individuals.

The aim of the analysis is to get insight into the extent to which a spillover effect exists in the United States. The focus is on the United States as a country is because the state level is the lowest geographical level about which information is available in this dataset of the BRFSS. An annual income variable is included in the BRFSS-dataset, which makes distinction between eight different income groups. An overview of these income groups and its quantities is shown in table 1.

Value /Group	Value Label	Frequency	Percentage
1	Less than $10,000	19,855	4.11
2	Between $10,000 and $14,999	21,838	4.53
3	Between $15,000 than $19,999	30,913	6.41
4	Between $20,000 than $24,999	37,943	7.86
5	Between $25,000 and $34,999	44,076	9.13
6	Between $35,000 and $49,999	58,349	12.09
7	Between $50,000 and $74,999	64,947	13.46
8	More than $75,000	127,081	26.34

Table 1. Overview of income groups and quantities in the BRFSS dataset (BRFSS, 2016).

As dependent variables, *the number of days mental health was not good,* and *number of days physical health was not good,* are used. These measures provide insight in the psychological, mental and physical well-being levels of people, which, according to a number of authors, is strongly affected by income inequality. This is explained in section 2.4.3. In addition to the income levels and the Gini coefficients, age, marital status, sex, U.S. state, employment and educational level are taken into account as independent variables.

The analysis partly builds further on the analysis of by Oswald and Wu (2009) who wrote the article "*Well-being across America: Evidence from a Random Sample of One Million U.S. Citizens*". For their research, they also used the BRFSS-dataset. The aim of their research was to analyse measures of life satisfaction and mental health of American citizens. One of the dependent variables, *mental distress*, is also used in this research. As independent variables, they used age, race, marital status, sex, U.S. state, employment and educational level. To find out which measures affect life satisfaction and mental health, Oswald and Wu conducted statistical analysis with a number of suitable regression models. One of their main conclusions is that there is no correlation between states' well-being and their GDP per capita.

In addition to the analyses of Oswald and Wu, this research is also interested in the income inequality as independent factor that influences mental health. This research is not focussing on the life satisfaction since this was an optional question in the survey of the dataset of 2016, which means that there are a lot of missing values. Instead, the number of days physical health was not good. is used as dependent variable. Another difference is that in this analysis, there is a focus on the *spillover effect.* As explained, the spillover effect means that not only the lower incomes experience negative outcomes due to income inequality, but also people with higher incomes. Therefore, *binary dummy variables* are created. Suits (1957) explains that a dummy variable is a variable that contains information which is not measurable on a numerical scale, such as sex, occupation, region etc. A dummy variable provides the opportunity to make a nominal variable measurable. The dummy variable which is used in this research is a binary variable and has two values: 0 and 1. This can for example mean absence or presence, yes or no, higher of lower etc. In this analysis the aim is to find out if higher incomes are also confronted by income inequality. Therefore several income dummy variables have been created, which show if someone has a lower or higher income than a particular value. When someone's income is higher than a particular value, the variable has a value of 1 and when it is lower, the value is 0. The values are based on the values of table 1. The following dummy variables have been created:

Variable Name	Meaning
Higher15000	Higher than $15,000
Higher20000	Higher than $20,000
Higher25000	Higher than $25,000
Higher35000	Higher than $35,000
Higher50000	Higher than $50,000
Higher75000	Higher than $75,000

Table 2. Name and meaning of income dummy variables.

As mentioned, when an income is lower than a particular amount it has the value of 0 and when it is higher, it has a value of 1. The reason it has been carried out this way, is because it provides insight in differences in number of days health was not good between income groups in states where the income inequality is higher or lower. To connect these dummy variables to income inequality, *interaction variables* are created. Ai and Norton (2003) explain that interaction terms are used to infer how the effect of one independent variable on the dependent variable depends on the magnitude of another independent variable. In this analysis, the aim is to get insight in how higher income levels are affected by income inequality with regards to their number of days health was not good. Therefore, interaction variables are created which consist of the interaction between the income dummies and the Gini-coefficients of a particular state. The influence of income inequality on the number of days health was not good across different income levels can be shown by using this method. In this way, insight can be obtained into the extent to which a spillover effect exists.

Several regressions have been conducted to get insight in the spillover effect. Special kinds of regressions have been carried out for these analyses, namely a *Tobit* estimator. The reason of this is because the histogram of the dependent variables *number of days mental health was not good* and *number of days physical health was not good* are right skewed since most people answer 0, which is the median of these two variables. In line with the research of Oswald and Wu (2009), who also used the BRFSS-dataset and *number of days mental health was not good* as dependent variable for their analyses, there is chosen to use a Tobit estimator. Oswald and Wu explain that by the nature of the data it is not possible for people with good mental health to distinguish themselves from people with sound mental health. Because of this, they used a Tobit estimator for their analyses. In addition to this, Pezzin et al. (2004) explain that a Tobit estimator is used when the distribution is non-normal, which is the case for the dependent variables in this analysis. They state that the Tobit estimator accounts for the data censoring, yielding unbiased and efficient estimates for the parameters. An additional argument for using a Tobit-model in the case when a lot of cases have a value of 0, was made by Fogarty (2018), who explains that a Tobit-model takes two kinds of observations into account: observations with a value of 0 (limit observations) and observations with a value greater than 0 (nonlimit observations). The Tobit estimator assumes that there is a fundamental difference when the dependent variable is equal to 0. In the Tobit model, the coefficient is calculated on the effects of observations in the dependent variable with a value greater than 0. Since most respondents answered that there number of days mental or physical health was not good was equal to 0, the Tobit estimator is suitable in order to conduct the analyses.

The software program *Stata* has been used to execute these regressions. The final aim is to get insight into the extent to which a spillover effect exists. However, it might be interesting to have a general idea of the influence of the state where someone is living and other factors on experienced mental and physical health before analysing the spillover effect.

The first regression only considers the differences between states. It is interesting to find out if differences exist between American states anyway, before looking at the Gini Coefficient at the state-level. Then, other predictors are added to the models. This should give insight into other factors than income inequality, which is added as predictor in later models. The first two models are conceptualized by the following equations:

$$Y= \beta 0 + \beta 1_{state} + R \tag{3.6}$$

$$Y = \beta 0 + \beta 1_{state} + \beta 2_{age} + \beta 3_{maritalstatus} + \beta 4_{sex} + \beta 5_{employment} + \beta 6_{education} + R \tag{3.7}$$

β0 is the intercept in this model. *Y* stands in this equation for *Number of Days Mental Health Not Good* and *Number of Days Physical Health Not Good.* Different regressions have been conducted with both dependent variables. *R* refers to the residual or error term. It should be noticed that all independent variables should be considered as dummy variables because all are nominal. This means that omitted reference categories have been used to make these variables measurable.

In addition to the equation above is in the following equation, the Gini-coefficient at the state level, added as independent variable to get insight in the relation between income inequality and *Number of Days Mental Health Not Good* and *Number of Days Physical Health Not Good.* The following equation indicates this model:

$$Y = \beta 0 + \beta 1_{state} + \beta 2_{age} + \beta 3_{maritalstatus} + \beta 4_{sex} + \beta 5_{employment} + \beta 6_{education} + \beta 7_{Gini\text{-}coefficient} + R \tag{3.8}$$

This model provides insight into the relation between income inequality and *Number of Days Mental Health Not Good* and *Number of Days Physical Health Not Good.* Also the change in Gini Coefficients between 2006 and 2016, and 2011 and 2016 are taken into account. These changes have been added as predictors to the model. The following model indicates this model:

$$Y = \beta 0 + \beta 1_{state} + \beta 2_{age} + \beta 3_{maritalstatus} + \beta 4_{sex} + \beta 5_{employment} + \beta 6_{education} + \beta 7_{Gini\text{-}coefficient} + \beta 8_{Gini\text{-}Change2006} + \beta 9_{Gini\text{-}Change2011} + R \tag{3.9}$$

However, the models above do not reveal information about the existence of a spillover effect. Therefore, in the following equation the interaction variable with the binary dummy income variable for income is included. The following equation indicates this model:

$$Y = \beta 0 + \beta 1_{\text{state}} + \beta 2_{\text{age}} + \beta 3_{\text{maritalstatus}} + \beta 4_{\text{sex}} + \beta 5_{\text{employment}} + \beta 6_{\text{education}} + \beta 7_{\text{Gini-coefficient}} + \beta 8_{(\text{IncomeHigher * Gini-Coefficient})} + R \tag{3.10}$$

This regression has been conducted for every single binary dummy variable as summarized in table 2.

All regressions above should provide insight in the extent to which the experienced mental and physical health of people in the U.S. are affected by the presence of people with higher or lower incomes. In other words, it should reveal the extent to which a spillover effect, as explained in section 2.5., exists.

4. Results

In this part of the research, the results of the different analyses are described and explained. Firstly, an overview of all Gini-Coefficients is provided which have the function of independent variable in other analyses of the research. Then, the results of the multilevel analysis, as described in section 3.3.2, are explained. Afterwards, there is elaborated on the outcomes of the regressions which should provide insight in the existence of a spillover effect.

4.1. Income inequality

In this first subsection, an overview of the Gini-Coefficients of the cities in Orange County, the counties in California and the states of the U.S. are shown in a table and mapped. These are the Gini-Coefficients from 2016 and are obtained from the Factfinder, which is a data-platform of the U.S. Census. Later in this research, these Gini-Coefficients are used as independent variables.

4.1.1. Cities Orange County

City	Gini-Coefficient
Anaheim	0.4307
Buena Park	0.3982
Costa Mesa	0.4429
Fullerton	0.4609
Garden Grove	0.4264
Huntington Beach	0.4436
Irvine	0.5010
Lake Forest	0.4013
Mission Viejo	0.3910
Newport Beach	0.5484
Orange	0.4455
Santa Ana	0.3998
Tustin	0.4393
Westminster	0.4637

Table 3. Overview of Gini-Coefficients of cities in Orange County (U.S. Census, 2017).

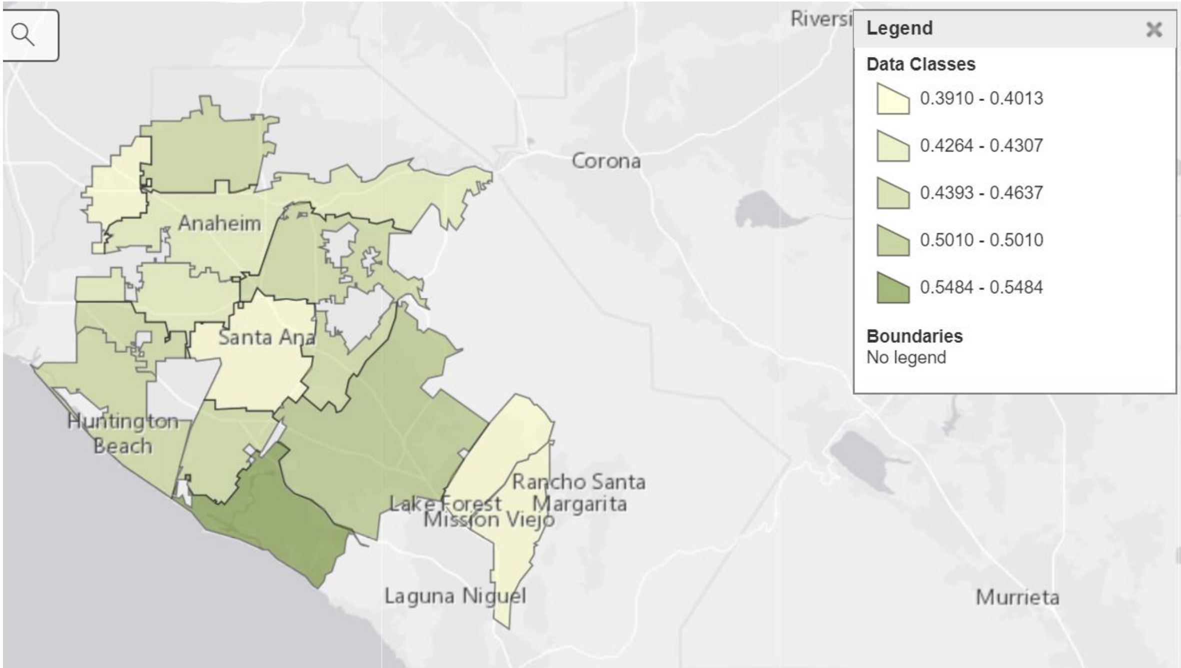

Figure 14. Map with the Gini-Coefficients of the cities in Orange County (U.S. Census).

The average Gini-Coefficient of Orange County is 0,4695. It stands out the Gini-Coefficients in the cities of Newport Beach and Irvine are relatively high. Lower rates of income inequality can be found in Santa Ana, Mission Viejo and Buena Park.

4.1.2. Counties California

County	Gini-Coefficient
Alameda County	0.4604
Los Angeles County	0.5030
Orange County	0.4695
Contra Costa Couny	0.4596
San Bernardino County	0.4400
Kern County	0.4644
San Diego County	0.4644
Butte County	0.4888
Sacramento County	0.4649
Fresno County	0.4910
Riverside County	0.4559
San Mateo County	0.4821
Solano County	0.4340
San Joaquin County	0.4466
Merced County	0.4969
Santa Clara County	0.4645
Stanislaus County	0.4532
Napa County	0.4641
Ventura County	0.4474
Shasta County	0.4655
Placer County	0.4571
Monterey County	0.4514
San Francisco County	0.5029
Santa Barbara County	0.4707

Sonoma County	0.4481
Tulare County	0.4554

Table 4. Overview of Gini-Coefficients of counties in California (U.S. Census, 2017).

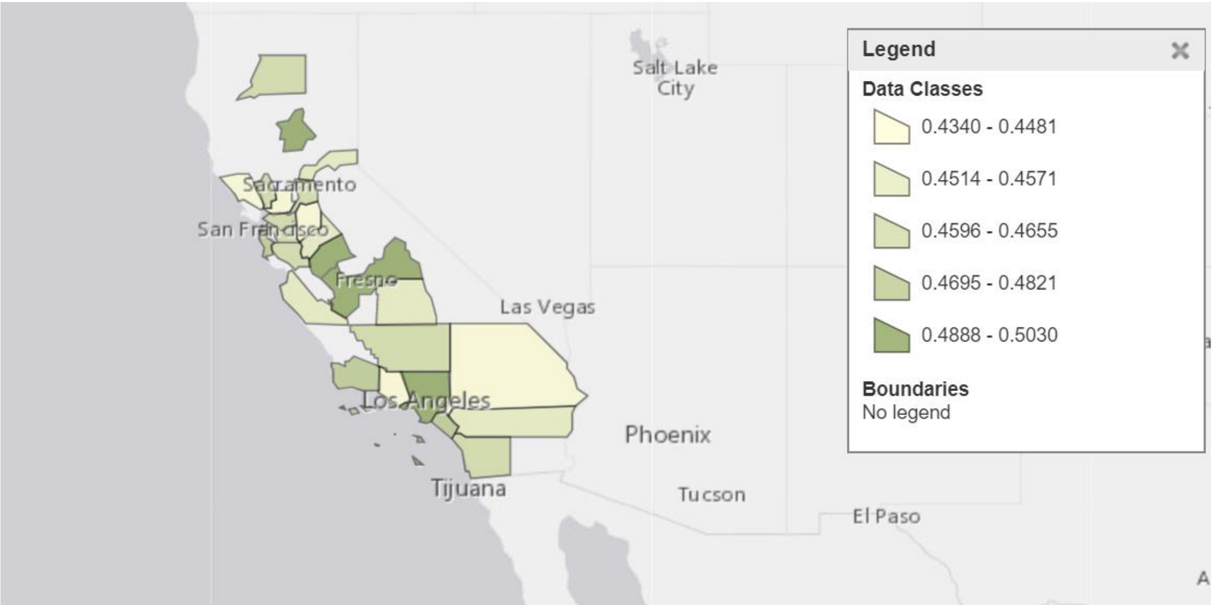

Figure 15. Map with the Gini-Coefficients of the counties in California (U.S. Census).

The average Gini-Coefficient of California is 0,4899. Table 4 shows that the Gini-Coefficients of counties with large cities, as Los Angeles and San Francisco are relatively high. Solano County has the lowest level of income inequality.

4.1.3. States U.S.A.

State	Gini-Coefficient
Alaska	0.4081
Alabama	0.4847
Arkansas	0.4719
Arizona	0.4713
California	0.4899
Colorado	0.4586
Connecticut	0.4945
Delaware	0.4522
Florida	0.4852
Georgia	0.4813
Hawaii	0.4420
Iowa	0.4451
Idaho	0.4503
Illinois	0.4810
Indiana	0.4527
Kansas	0.4550
Kentucky	0.4813
Louisiana	0.4990
Massachusetts	0.4786
Maryland	0.4499
Maine	0.4519

Michigan	0.4695
Minnesota	0.4496
Missouri	0.4646
Mississippi	0.4828
Montana	0.4667
North Carolina	0.4780
North Dakota	0.4533
Nebraska	0.4477
New Hampshire	0.4304
New Jersey	0.4813
New Mexico	0.4769
Nevada	0.4577
New York	0.5129
Ohio	0.4680
Oklahoma	0.4645
Oregon	0.4583
Pennsylvania	0.4689
Rhode Island	0.4781
South Carolina	0.4735
South Dakota	0.4495
Tennessee	0.4790
Texas	0.4800
Utah	0.4263
Virginia	0.4705
Vermont	0.4539
Washington	0.4591
Wisconsin	0.4498
West Virginia	0.4711
Wyoming	0.4360

Table 5. Overview of Gini-Coefficients of states in the U.S.A (U.S. Census, 2017).

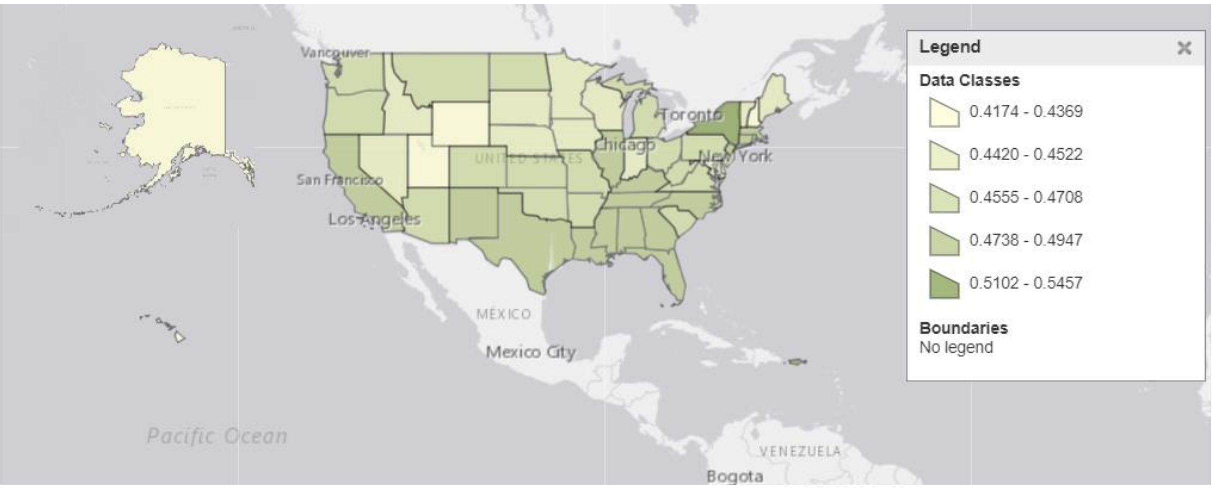

Figure 16. Map with the Gini-Coefficients of the states in the U.S.A. (U.S. Census).

The average Gini-Coefficient of the United States is 0,4824. Relatively high levels of income inequality can be found in New York and Louisiana. States with lower Gini-coefficients are Alaska, New Hampshire, Utah and Wyoming.

4.2. Multilevel Analysis at Three Different Levels: Orange County, California and the United States

This section presents the results of the multilevel analyses and the regressions for the mental and physical health-measures. Firstly, a regression has been conducted to get insight in the relationship between these dependent variables and the *Gini Coefficient* at the *Census Tract level, Gini Coefficient* at the level of the *city* (for the analysis at the County-level), *county* (for the analysis at the state-level) and *state* (for the analysis at the country-level), *median income, work force ratio, unemployment, rate of people below the poverty line, median gross house rent, rate of people who graduated high school* and the *Gini Coefficient* at the level of the *city* (for the analysis at the County-level), *county* (for the analysis at the state-level) and *state* (for the analysis at the country-level). As explained before, the data used in this analysis are averages of Census Tracts. In this first analysis, the contextual factor is not taken into account, only the influence of income inequality and other predictors are taken into account. The second model is the *null model* where only the contextual factor is taken into account and all other predictors are left out of the model. In this model it is analysed whether it matters in which city, county or state, people in a census-tract are living with regards to the mental and physical health well-being. In the last model, both the contextual factor and the predictors are taken into account. The micro-units in these analyses are Census Tract-averages and the analyses have been carried out at the level of Orange County, California and the United States. Furthermore, there are conducted different analyses for two dependent variables: *percentage of respondents who report that 14 or more days during the past 30 days during which their mental health was not good* and *percentage of respondents who report 14 or more days during the past 30 days during which their physical health was not good.* In the remainder, these two variables are named *mental health* and *physical health.* There is chosen to use the natural log of the dependent variables since the values are not normally distributed (see appendix 1). Nelder & Baker (2004) explain that in order to conduct a regression, the values of a dependent variable need to be normally distributed. The natural log of this variable can be used as dependent variable when there is no normal distribution. In the case of these particular variables, a normal distribution comes forward when the natural log is used. This is shown in appendix 1.

4.2.1. Regression Models

The models of this section exist of regressions to get insight in the relationship between *mental* and *physical health* and a number of predictors: *Gini Coefficient* at the *Census Tract level, Gini Coefficient* at the level of the *city* (for the analysis at the county-level), *county* (for the analysis at the state-level) and *state* (for the analysis at the country-level), *median income, work force ratio, unemployment, rate of people below the poverty line, median gross house rent, rate of people who graduated high school* and the *Gini Coefficient* at the level of the *city* (for the analysis at the County-level), *county* (for the analysis at the state-level) and *state* (for the analysis at the country-level). As mentioned, the contextual effect is not taken into account in these regressions. The equations of these regressions are represented by equation 3.1. The micro-units in this model are averages of Census Tracts. The outcomes of these models with *mental health* as dependent variable for the three geographical levels are shown in tables 6, 7 and 8.

Natural Log *Mental Health* County level	Coef.	Std. Err.	T	P>t	[95% Conf.	Interval]	Number of obs	463
Gini Coefficient of City	-.3933977	.1249098	-3.15	0.002	-.6388707	-.1479246	F(8, 454)	419.66
Gini at Census Tract Level	-.2605848	.0894923	-2.91	0.004	-.4364553	-.0847143	Prob > F	0.0000
Median income	.0000702	.000025	2.80	0.005	.000021	.0001194	R-squared	0.8809
Gross Rent House	-.0000643	.000012	-5.37	0.000	-.0000878	-.0000408	Adj R-squared	0.8788
Labor Force Participation Rate	.004344	.0005838	7.44	0.000	.0031967	.0054914		
Unemployment Rate	.0039802	.0014109	2.82	0.005	.0012074	.0067529		
Percentage graduated high school	-.0074002	.0003958	-18.70	0.000	-.0081781	-.0066223		
Percentage below poverty level	.0079046	.000654	12.09	0.000	.0066194	.0091899		
Constant	2.977326	.0719703	41.37	0.000	2.83589	3.118763		

Table 6. Regression that shows the relationship between the natural log of *mental health* and a number of predictors at county level.

Natural Log *Mental Health* State level	Coef.	Std. Err.	T	P>t	[95% Conf.	Interval]	Number of obs	5,185
Gini Coefficient of County	-.5689884	.0625171	-9.10	0.000	-.6915482	-.4464285	F(8, 5176)	4273.26
Gini at Census Tract Level	-.529834	.0265273	-19.97	0.000	-.5818387	-.4778293	Prob > F	0.0000
Median income	-2.36e-06	8.47e-08	-27.85	0.000	-2.52e-06	-2.19e-06	R-squared	0.8685
Gross Rent House	-.000046	4.80e-06	-9.59	0.000	-.0000554	-.0000366	Adj R-squared	0.8683
Labor Force Participation Rate	.0013491	.0001771	7.62	0.000	.0010018	.0016963		
Unemployment Rate	.0047364	.0003707	12.78	0.000	.0040095	.0054632		
Percentage graduated high school	-.0062688	.0001312	-47.78	0.000	-.006526	-.0060116		
Percentage below poverty level	.0059887	.0002033	29.46	0.000	.0055902	.0063872		
Constant	3.478807	.032877	105.81	0.000	3.414354	3.54326		

Table 7. Regression that shows the relationship between the natural log of mental health and a number of predictors at state level.

Natural Log *Mental Health* Country Level	Coef.	Std. Err.	T	P>t	[95% Conf.	Interval]	Number of obs	26,394
Gini Coefficient of State	1.03497	.0442499	23.39	0.000	.9482377	1.121702	F(8, 26385)	15403.27
Gini at Census Tract Level	-.528976	.0122452	-43.20	0.000	-.5529773	-.5049747	Prob > F	0.0000
Median income	-3.23e-06	4.90e-08	-65.89	0.000	-3.33e-06	-3.14e-06	R-squared	0.8236
Gross Rent House	-.0000235	2.61e-06	-9.04	0.000	-.0000287	-.0000184	Adj R-squared	0.8236
Labor Force Participation Rate	.0007321	.0000841	8.70	0.000	.0005672	.000897		
Unemployment Rate	.0060644	.0001492	40.65	0.000	.005772	.0063568		
Percentage graduated high school	-.0050608	.0000742	-68.24	0.000	-.0052061	-.0049154		
Percentage below poverty level	.0066651	.0000942	70.79	0.000	.0064805	.0068496		
Constant	2.654767	.0235462	112.75	0.000	2.608615	2.700919		

Table 8. Regression that shows the relationship between the natural log of *mental health* and a number of predictors at county level.

In order to keep the paper legible, it has been decided to show only these first three tables in the text of this section. The remaining tables are attached as appendixes.

All predictors in the models in table 6, 7 and 8 are significant at a 95% confidence level. The model indicates that all the predictors have a significant influence on mental health, regarding the averages of Census Tracts. Having a look at the Gini-Coefficients, the majority of the results are not in line with the expectations, based on the theories, discussed in section 2.4.3. Wilkinson and Pickett (2010) show in their book evidence that a relationship between the mental health level and income inequality exists. They show that when income inequality in a country or state is higher, the mental health level is lower in this country or state: there are more people with mental illnesses. This way of thinking is in line with the relationship between *mental health* and '*Gini at State level*', which stands out in the model results at the country level (table 8). There is a positive relationship between these variables which indicates that the average number of people who report that more than 14 days mental health was not good the 30 days before they completed the survey, is higher when the income inequality level is higher. The natural log of *mental health* increases by 103,50% when Gini Coefficient increases by one, which is equal to an increase in the coefficient by 103,56%. It should be taken into account that the Gini-Coefficient is a number between 0 and 1, thus an increase by one could be considered as the extreme. In contrast to this increase, all other Gini Coefficients variables at the county- and city- level, and also at the level of Census Tract level for all three models, have negative coefficients. This means that an increase in the Gini Coefficient results in a lower average of people who report that more than 14 days, their mental health was not good. This model outcome is not in line with the processes described in the theoretical framework. Other mechanisms that influence the mental health may play a more important role at these scale levels than the mechanisms described in section 2.4.3.

The same analyses are done with *physical health* as dependent variable for the three geographical levels and the tables, of which the results are shown in appendix 2.

Using *physical health* as dependent variable, instead of *mental health* provides a similar pattern. Almost all predictors are significant, except for Gini at Census Tract-level, the median income and the percentage below poverty level in the county-level model. Fiscella and Franks (2000), Kawachi and Kennedy (1999) and Wilkinson and Pickett (2010) explain mechanisms of income inequality resulting in a lower level of physical health. This is explained in section 2.4.3. Wilkinson and Pickett also show a relationship at the level of countries and states between income inequality and physical health related factors as life expectancy and infant deaths, which is also explained in the second section. Based on this, it might be expected that higher levels of income inequality result in lower physical health levels. A higher level of income inequality might result in a higher Census-Tract average of people who report that more than 14 days their physical health was not good. Similar to the model where mental health was used as dependent variable, only the coefficient of the Gini at the state-level supports this idea. A positive relationship exists between the *physical health-variable* and income inequality, which is significant at a 95% confidence level. The natural log of *physical health*, at the country level increases by 101,15% when Gini Coefficient increases by one, which is equal to an increase in the coefficient by 101,16%. This indicates that an increase in the Gini-Coefficient at state level results, on average, in more people reporting that their physical health was not good more than 14 days in the 30 days before they completed the survey. In contrast to this increase, all other Gini Coefficients variables at the county- and city- level, and also at the level of Census Tract level for all three models, show negative coefficients, and as mentioned, the Gini Coefficient at the level of the Census Tract in the county-model is not significant. Negative coefficients indicate that a higher level of income inequality results in more people, as average of the Census Tract, reporting that more than 14 days in the 30 days before they completed the survey, their physical health was not good. This outcome does not correspondent with the processes described by the authors mentioned above. Other mechanisms that influence the physical health at Census Tract-level may play a more important role at these geographical levels than the mechanisms, related to income inequality, as described in section 2.4.3.

4.2.2. Null Models

In the following models, the geographical context is taken into account. Before linking the geographical context to income inequality and other predictors, it may be of interest to find if there exists a contextual effect anyway. The independent variables therefore have been left out of consideration in these first models. The focus of these models is only on the geographical context. An HLM-model without predictor variables is called a 'null model' (Short et al. 2005). This null-model is represented by equation 3.2. The aim of the HLM models is to calculate the Intraclass Correlation which reveals in the amount of variance explained by group-level (city, county or state) effects, this has been more elaborately explained in the third section. The equation for the Intraclass Correlation is represented by equation 3.5. The analyses have been carried out for every geographical level: county, state and country. Besides, *mental health* and *physical health* represented by averages of the Census Tracts, have been used as dependent variables. The outcomes of the intraclass correlation models with the natural log of *mental health* as dependent variable are shown in appendix 3.

The intraclass correlation has the highest level at the city-level. 34,12% of the variation in the natural log of mental health, is explained by the city where people in a census tract are living, according to this model. The intraclass correlations for the models at the state and country-level are lower. Respectively 22,14% and 20,57% of the variation in the natural log of *mental health*, can be explained by the county and state where people in a census tract are living, considering the models in appendix 3.

The same analyses have been conducted for the dependent variable *physical health.* The outcomes are shown in appendix 4.

The models with the natural log of *physical health* as dependent variable show a similar pattern as the models with the natural log of mental health as dependent variable. The intraclass correlation is at the highest level at the city-level. 38,09% of the variation in the natural log of physical health is explained by the city where people in a census tract are living, according to this model. The intraclass correlations for the models at the state and country-level are lower. Respectively 20,87% and 16,40% of the variation in the natural log of physical health, can be explained by the county and state where people in a census tract are living, considering the models in appendix 4. In the next subsection, predictors have been added to this model.

4.2.3. Multilevel Analyses with Predictors

In this model, the predictors which have been used in section 4.2.1. are added to the multilevel models of section 4.2.2. The equation of this model is represented by equation 3.3. The aim is to find out if the regression coefficients change when the contextual effect is taken into account and to find out if the intraclass correlation changes when the predictors are taken into account. The analyses have again been conducted for all three geographical levels and both dependent variables where the micro-units are averages of Census Tracts. In appendix 5, the outcomes of the regressions and the intraclass correlations have been shown for the natural log of the dependent variable *mental health*.

The intraclass correlations of the county-model and the state-model are lower when the predictors are added to the model. In the case of the county-model, 20,95% of the variance in the natural log of the variable *mental health* is explained by the average of a Census Tract when the predictors are added to the model, in contrast to 34,12% when the predictors are not added to the model. In this model, the Gini Coefficient at city-level is not significantly having influence on *mental health*. In the case of the state-model, 18,04% of the variance in the natural log of *mental health* has been explained by the county where a Census Tract is located when the predictors are added to the model, in contrast to 22,14% when the predictors are not added to the model. All predictors in these two models, with exception of Gini Coefficient at city-level, are significant at a 95% confidence interval level and these predictors result in a lower geographical effect on the average number of people who report that their mental health was not good for more than 14 days in the in the 30 days before they completed the survey. The Gini-coefficients at the level of county and Census Tract in the two models show negative coefficients which are significant at 95% confidence interval, which indicates that the average number of people who report that their mental health was not good for more than 14 days in the 30 days before they completed the survey, decreases, when income inequality increases. This is also the case for the Gini-Coefficient at Census Tract level in the country model.

In contrast to the county- and state-model, the intraclass correlation of the country-model increases when the predictors are added to the model. In the model where predictors are added, 43,69% of the variance in the natural log of number of days that mental health was not good is explained by the state where a Census Tract is located, in contrast to 20,57% when predictors are not added to the model. Even more so, the coefficient of Gini Coefficient at state level increases when the geographical context has been taken into account in contrast to the regression model of 4.2.1. The coefficient increases from 1.05 to 1.49. In both cases, the average number of people who report that their mental health was not good for more than 14 days in the in the 30 days before they completed the survey, increases when income inequality increases. Also the state-effect is stronger than the city- and county- effect when predictors have been added to the model. According to these models, the positive influence of income inequality on the average number of people who report that their mental health was not good for more than 14 days in the in the 30 days before they completed the survey, matters at the state level, which is in line with the evidence created by Wilkinson and Pickett (2010), Kawachi and Kennedy (1999) and Sturm and Gresenz (2002). These authors found evidence that a negative relationship between income inequality and mental health levels exists. Wilkinson and Pickett show in their book that when income inequality in a country or state is higher, the mental health level is lower in this country or state: there are more people with mental illnesses. This is in line with the last model at the country-level. However, at lower geographical levels, this relationship does not stand out. The mechanism described in 2.4.2. and 2.4.3. fuels the expectation that income inequality at lower geographical levels matters. In these sections it has been described that in areas with higher levels of income inequality, this inequality results in *more status anxiety, lower levels of trust, less social capital, less social cohesion* and *more class conflicts,* which results in higher levels of stress, frustration and lower levels of mental health. This is mainly a mechanism that has impact on the direct surrounding of a group of people. Based on this mechanism, one might expect that at lower geographical levels, income inequality has more influence on the average mental well-being level in a Census Tract. However, this model does not correspondent with this explanation. The models in appendix 5 imply that other mechanisms or factors have a more important influence on the mental well-being at lower geographical levels.

In appendix 6, the outcomes of the regressions and the intraclass correlations have been shown for the natural log of the dependent variable *physical health*.

A similar pattern comes forward when *physical health* has been used as dependent variable instead of *mental health.* The intraclass correlations for the county- and state-model decrease when predictors are added to the model. In the case of the county-model, 17,96% of the variance in the natural log of *physical health* has been explained by the city where a Census Tract is located, when the predictors are added to the model, in contrast to 38,09% when the predictors are not added to the model. In this model, the Gini Coefficient at city-level and Census Tract-level is not significantly having an influence on the *physical health*. In the case of the state-model, 10,57% of the variance in the natural log of *physical health* is explained by the county where people in a Census Tract are living, when the predictors are added to the model, in contrast to 20,87%, when the predictors are not added to the model. In this case, the Gini-level at Census Tract is not having a significant influence on the natural log of *physical health*. The model indicates that the Gini Coefficient at county level is significant at a 95% confidence interval level. This relation in this model is negative, which implies that when the level of income inequality is increasing, the natural log of the average number of people who report that their mental health was not good for more than 14 days in the in the 30 days before they completed the survey, is decreasing. This also goes for the Gini Coefficient at Census Tract level in the country-model. All other variables in both models are significant. The models imply that these variables are more of interest than the city or county where a Census Tract is located.

In line with the previous model where *mental health* was used as dependent variable, the intraclass correlation of the country-model increases when the predictors are added to the model. In the model where predictors are added, 21,53% of the variance in the natural log of *physical health* has been explained by the state where a Census Tract is located, in contrast to 16,40% when predictors are not added to the model. The coefficient of income inequality at state level increases, relatively to the regression model of section 4.2.1., when the geographical context has been taken into account by using a multilevel model. The coefficient increases from 1.01 to 1.20. In both cases, the average number of people who report that their mental health was not good for more than 14 days in the in the 30 days before they completed the survey, increases. Even more so, the state-effect is stronger than the city- and county- effect when predictors are added to the model. According to these models, the positive influence of income inequality on the average number of people who report that their mental health was not good for more than 14 days in the in the 30 days before they completed the survey, matters at the state level, which is in line with the evidence created by Wilkinson and Pickett (2010). Kawachi and Kennedy (1999), Sturm and Gresenz (2002), Fiscella and Franks (2000) who demonstrate evidence of a negative relation of physical health levels and income inequality. According to the models in appendix 6, this only goes for the country-level and not at lower geographical levels, such as the state- and county-level. The mechanism that explains the relationship between income inequality and physical health, described in section 2.4.3., is similar to the mechanisms which explain the relationship between income inequality and mental health. Authors as Wilkinson and Pickett (2010) and Kawachi and Kennedy (1999) claim that the reduced mental health by income inequality also results in a decreasing physical health level. They explain that *job status, limited possibilities, social capital, stress, anxiety, frustration, social comparisons* are factors that influence mental health which subsequently results in more vulnerability for physical health problems. For an important part, this is caused because people in lower social classes who are confronted by large income differences, are more likely to be obese, to smoke, to have higher blood pressure and to be less physically active. Wilkinson and Pickett claim that the most important factor is job stress and sense of control people have over their work, reinforced by the large differences between people from different socio-economic statuses. They claim that the psychological well-being of people has a direct impact on the physical health, as explained in section 2.4.3. The mechanisms above would imply that income inequality has an impact on the direct surrounding of a group of people. Based on these mechanisms, one might expect that at a lower geographical level, income inequality has more influence on the average physical well-being in a Census Tract. However, this model does not correspondent with this assumption. The models in appendix 6 imply that other mechanisms or factors have a more important influence on the physical well-being at lower geographical levels.

4.3. U.S. State analysis - Spillover Effects

The main objective of this research is to find out if a spillover effect exists to a certain extent. A spillover effect, explained in section 2.5, means that not only the poor incomes experience negative outcomes due to income inequality, but also people with higher incomes. In section 3.3.3., a way has been described to find out to which extent a spillover effect exists. The equations 3.6 to 3.12 have been created in order to get insight in this spillover effect. Several Tobit regressions have been carried out for these analyses.

4.3.1. Regressions between Health and States

Before getting insight in the relationship between health-levels and the level of inequality, it is interesting to find out if differences exist in the health-levels between the different states. Oswald and Wu (2009) showed differences in well-being levels across states in their research. Table 9 shows the outcome of a Tobit model that shows the relationship between *the number of days mental health* and *physical was not good* and the state where an individual is living. Since this research is partly focused on California, this state is used as reference category. Furthermore, other factors which could affect health-levels have been taken into account in section 4.3.2.

Number of days mental health was not good	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**	Number of obs	469,861
State (ref. cat. California)							LR chi2(50)	1409,49
Alabama	.7073014	.1185145	5.97	0.000	.4750167	.9395861	Prob > chi2	0
Alaska	-.4085109	.1625463	-2.51	0.012	-.7270966	-.0899252	Pseudo R2	0,0004
Arizona	-.2623985	.1042256	-2.52	0.012	-.4666775	-.0581195		
Arkansas	.5113549	.1298301	3.94	0.000	.256892	.7658178		
Colorado	-.4828516	.0968719	-4.98	0.000	-.6727175	-.2929857		
Connecticut	-.5037871	.1040246	-4.84	0.000	-.7076722	-.2999021		
Delaware	-.2764277	.14276	-1.94	0.053	-.556233	.0033775		
District of Columbia	-.2731564	.1456992	-1.87	0.061	-.5587224	.0124095		
Florida	-.0023217	.0834664	0.03	0.978	-.1659132	.1612698		
Georgia	-.2227127	.1291623	-1.72	0.085	-.4758668	.0304414		
Hawaii	-.6526665	.1130244	-5.77	0.000	-.8741909	-.4311421		
Idaho	-.1614542	.1302441	-1.24	0.215	-.4167286	.0938202		
Illinois	-.3719777	.1343006	-2.77	0.006	-.6352028	-.1087526		

Indiana	-.0707096	.1040734	0.68	0.497	-.2746902	.1332711
Iowa	-.7867512	.1170512	-6.72	0.000	-1.016.168	-.5573344
Kansas	-.6587482	.1016204	-6.48	0.000	-.8579211	-.4595754
Kentucky	.5156988	.1060371	4.86	0.000	.3078693	.7235282
Louisiana	.2951067	.1301487	2.27	0.023	.0400193	.550194
Maine	-.0539904	.1067013	0.51	0.613	-.2631217	.1551408
Maryland	-.4220956	.0927259	-4.55	0.000	-.6038356	-.2403556
Massachusetts	.0589114	.1123618	0.52	0.600	-.1613143	.2791371
Michigan	.2097332	.1018013	2.06	0.039	.0102058	.4092606
Minnesota	-.8183631	.0944575	-8.66	0.000	-1.003497	-.6332294
Mississippi	.2330834	.1318186	1.77	0.077	-.0252768	.4914437
Missouri	.2250403	.1177756	1.91	0.056	-.0057962	.4558768
Montana	-.5126922	.124549	-4.12	0.000	-.7568044	-.26858
Nebraska	-.805343	.0964286	-8.35	0.000	-.9943401	-.6163459
Nevada	.4617781	.1390939	3.32	0.001	.1891584	.7343978
New Hampshire	-.2204497	.1215525	-1.81	0.070	-.4586889	.0177895
New Jersey	-.2341457	.1153333	-2.03	0.042	-.4601954	-.0080959
New Mexico	.0901007	.1240388	0.73	0.468	-.1530115	.3332129
New York	-.0269665	.0842518	0.32	0.749	-.1920974	.1381643
North Carolina	.1667955	.1208983	1.38	0.168	-.0701614	.4037524
North Dakota	-1.206616	.1261834	-9.56	0.000	-1.453.931	-.9593004
Ohio	-.0323808	.1011173	0.32	0.749	-.2305675	.1658059
Oklahoma	.2741347	.1189811	2.30	0.021	.0409355	.507334
Oregon	.3253664	.1287153	2.53	0.011	.0730884	.5776444
Pennsylvania	.2701829	.1192681	2.27	0.023	.0364211	.5039447
Rhode Island	.2213963	.1283485	1.72	0.085	-.0301628	.4729553
South Carolina	.3715802	.103647	3.59	0.000	.1684352	.5747252

South Dakota	-.9883842	.1259538	-7.85	0.000	-123.525	-.7415187
Tennessee	.7000249	.1234723	5.67	0.000	.458023	.9420269
Texas	-.3932792	.1026616	-3.83	0.000	-.5944927	-.1920656
Utah	-.2148308	.1041567	-2.06	0.039	-.4189747	-.0106869
Vermont	.0344188	.1208565	0.28	0.776	-.2024562	.2712938
Virginia	-.3759648	.1099024	-3.42	0.001	-.5913701	-.1605595
Washington	-.2548673	.0978175	-2.61	0.009	-.4465867	-.063148
West Virginia	1.1101	.1176153	9.44	0.000	.8795772	1.340.622
Wisconsin	-.3717589	.1295576	-2.87	0.004	-.6256877	-.1178301
Wyoming	-.6260507	.1372051	-4.56	0.000	-.8949685	-.3571329
Constant	3.579869	.072852	49.14	0.000	3.437081	3.722657

Table 9. Tobit regression between number of days mental health was not good and the state where an individual is living.

In order to keep the paper legible, it has been decided to show only these first table in the text of this section. The remaining tables have been attached as appendices.

Not all states differ significantly from California on a 95% confidence level. States where people have significantly more days that mental health was not good, are Alabama, Arkansas, Kentucky, Louisiana, Michigan, Nevada, Oklahoma, Oregon, Pennsylvania, South Carolina, Tennessee and West Virginia. West Virginia, Alabama and Tennessee have the highest coefficients in this model, which associates that people in these states have the most days that mental health was not good, compared to California. States where people have significantly less days that mental health was not good, are Alaska, Arizona, Connecticut, Hawaii, Illinois, Iowa, Kansas, Maryland, Minnesota, Montana, Nebraska, New Jersey, South Dakota, Texas, Utah, Virginia, Washington, Wisconsin and Wyoming. According to the coefficient, individuals in Iowa, both Dakota's, Minnesota, Nebraska and Wyoming have the least days that mental health was not good. Oswald and Wu (2009) conducted the same kind of analysis. However, they did this with an older dataset (data from 2005 to 2008) and they used Alabama as reference category. A striking result was that there was not any single state which had significantly more days that mental health was not good than Alabama in this research. This is partly in line with the results found in this research. Only the state of West-Virginia shows more days that mental health was not good experienced by an individual. The self-assessed health in West-Virginia, however, was not significantly different from Alabama in the results provided by Oswald and Wu. The same goes up for Tennessee, which also has an strikingly high significant coefficient in the model used in this research. Another similarity between this research and the research of Oswald and Wu is that Iowa, Nebraska and both Dakotas have the highest self-assessed health compared to the reference categories. In Minnesota, the self-assessed health is also significantly better than the reference category in the model used by Oswald and Wu, but does not stand out as much as in the model used in this study. A difference with respect to the outcomes is that in the study by Oswald and Wu, Louisiana is one of the states with the highest level of self-assessed mental health. However in this study, the self-assessed health of Louisiana is not significantly different from the reference category, California.

Looking at the number of days that physical health was not good instead of mental health, some differences come forward. Again, not all the states are significantly different from California at a 95% confidence interval. States where people have significantly more days that physical health was not good comparing to California, are Alabama, Alaska, Arkansas, Florida, Georgia, Idaho, Illinois, Indiana, Kentucky, Louisiana, Michigan, Maine, Mississippi, Missouri, Montana, Nevada, New Jersey, New Mexico, New York, Ohio, Oklahoma, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Washington, West Virginia and Washington. The states which have the highest coefficients are West Virginia, Kentucky and Tennessee. According to the model, people in these states have the most days that physical health was not good, comparing to California. States where people have significantly less days that physical health was not good, are Iowa, Kansas, Minnesota, Nebraska, North Dakota and the District of Columbia. The state where people have the least days that physical health was not good, compared to California, is North Dakota.

The model in appendix 7 shows that there are differences across states in mental and physical health levels. From section 4.3.3. and onwards is shown that the level of income inequality at the state level explains these differences and building on this, the final aim is to find out to what extent a spillover effect exists.

4.3.2. Regressions without Gini-Coefficient

As already explained, this analysis included other factors to obtain a better insight into which other variables may have influence on the number of days mental and physical health was not good of individuals. In section 2.7., a number of factors that affect health and well-being have been discussed. The influence of some of the factors have been analyzed in this section. Firstly, analyses have been carried out with *number of days mental health was not good* as dependent variable. The outcomes of these analyses have been shown in appendix 8 (table 33). Most variables are significant at a 95% confidence level, and several things come forward.

The model outcomes show that females have more days than males that mental health was not good, which is significant on a 95% confidence level. Looking at the age group, the model shows that people between 25 and 29 have significantly more days that mental health was not good. People in the age groups of 45 years and older have increasingly less days that mental health was not good, which is significant on a 95% confidence level. With regards to employment status, the model shows that people who are employed, are self-employed, are student, are homeowner, are retired or are less than one year out of work, have less days that mental health was not good than people who are out of work for more than one year. People who are unable to work have more days that mental health was not good. For people who are employed and self-employed, this coefficient is the highest. Even more so, the models show that married people have less days that mental health was not good. Looking at education, people who followed elementary, some high school or some college or technical school have more days that mental health was not good, which is significant on a 95% confidence interval. As described in section 2.7., Oswald and Wu conducted similar analyses with an older dataset (data from 2005-2008). The outcomes of this research are broadly comparable. However, one striking difference is that in the model used by Oswald and Wu, it comes forward that when age is increasing, the level of self-assessed health is decreasing. In this research, it is shown that people from older age classes experience significantly less days that mental health was not good. A difference is that Oswald and Wu used age as ratio-variable and this study uses age as categorial variable: age is divided in a number of groups. However, it is remarkable that the direction of the significant relationship is opposite.

The same analyses have been conducted with *number of days physical health was not goo*d as dependent variable. The tables for this regression have been shown in table 34 (appendix 8).

Looking at *married, sex,* and *employment* status, the pattern is similar to the pattern when *number of days mental health was not good* is used as dependent variable. Differences come forward with regards to age groups: when number of days physical health was not good is used as dependent variable, people from older age groups have more days that physical health was not good. With regards to *education*, no pattern comes forward, the only thing that stands out is that people who graduated college have less days that physical health was not good.

4.3.3. Regressions with Gini-Coefficient

In this section, the same analyses as above, have been carried out with Gini-Coefficient added as independent variable. In the first model which included both the state and the Gini-Coefficient, Gini was omitted because of collinearity. Because the Gini-coefficients are at the state-level, the variable *state* has been omitted in the model. The analyses have been conducted for both dependent variables: *number of days that mental health was not good* and *number of days physical health was not good.* Appendix 9 shows the outcomes of these models.

For these both dependent variables, a positive relationship comes forward between the variables and the Gini-coefficient, which is significant on a 95% interval confidence. This means that when income inequality increases, individuals experience more days that mental and physical health are not good. The coefficients are respectively 1.13 and 1.89 for *mental* and *physical* health. This relation is similar to the outcomes of the multilevel analyses, which are explained in 4.2., and is also in line with the evidence created by Sturm and Gresenz (2002), Wilkinson and Pickett (2010), Kawachi and Kennedy (1999), Sturm and Gresenz (2002) and Fiscella and Franks (2000), who found evidence of a negative influence of income inequality on mental and physical health-level, as explained in sections 2.4.3. and 4.2.3.

4.3.4. Time-Effect

In addition to the influence of income inequality, the change of the Gini-Coefficient is taken into account in the following analyses, since the influence of income inequality on mental and physical health is described as a *process* with a number of *mechanisms,* in terms of factors, such as *status anxiety, levels of trust, social capital, social cohesion, class conflicts, job status, limited possibilities, frustration* and *social comparisons*, as explained in sections 2.4.2. to 2.4.4.. The change of the Gini-Coefficient between 2006 and 2016 and between 2011 and 2016 has been considered. Table 10 shows an overview with the changes in Gini-Coefficient for every American State.

State	Change 2011-2016	Change Gini 2006-2016
Alabama	0.0034	0.0049
Alaska	0.0075	0.0004
Arizona	0.0082	0.0142
Arkansas	0.0024	0.0108
California	0.0068	0.022
Colorado	0.0002	0.009
Connecticut	0.0088	0.0147
Delaware	0.0084	0.0148
Florida	0.0041	0.0182
Georgia	0.0046	0.0206
Hawaii	0.0068	-0.0011

Idaho	0.0137	0.0247
Illinois	0.0071	0.0169
Indiana	0.0033	0.0174
Iowa	0.0082	0.0182
Kansas	0.0113	0.0145
Kentucky	0.0032	0.0141
Louisiana	0.0067	0.0153
Maine	0.0006	0.0235
Maryland	0.0047	0.0183
Massachusetts	0.0055	0.0216
Michigan	0.0036	0.0208
Minnesota	0.0054	0.019
Mississippi	0.0064	0.0089
Missouri	0.0021	0.0142
Montana	0.0236	0.0327
Nebraska	-0.0047	0.012
Nevada	-0.0004	0.0182
New Hampshire	-0.0003	0.0174
New Jersey	0.0088	0.0202
New Mexico	-0.0067	0.0184
New York	0.0069	0.0152
North Carolina	0.0032	0.0168
North Dakota	0.0138	0.0246
Ohio	0.0047	0.0151
Oklahoma	0.0039	0.0052
Oregon	0.0026	0.0172
Pennsylvania	0.0069	0.013
Rhode Island	0.0064	0.0318
South Carolina	0.0042	0.007
South Dakota	0.0114	0.0048
Tennessee	0.003	0.0106
Texas	0.0032	0.0063
Utah	0.0012	0.0161
Vermont	0.0127	0.0235
Virginia	0.0041	0.0113
Washington	0.0111	0.013
West Virginia	-0.01	0.0151
Wisconsin	0.0065	0.0195
Wyoming	0.0198	0.0149

Table 10. Overview of changes between 2006-2016 and 2011-2016 in the Gini-coefficient for every state

Table 10 shows that in most states the level of income inequality increased. Between 2006 and 2016, it increased in every state, except for Hawaii. Between 2011 and 2016 the level of income inequality increased in most states. Only in the states Nebraska, Nevada, New Hampshire, New Mexico and West Virginia, the level of income inequality decreased. In the following models this change is added as predictor of the number of days mental and physical health were not good. The outcomes of these models have been shown in appendix 10.

Looking at the influence of the change in Gini-Coefficients, it stands out that there is a negative relationship between the change in the Gini-Coefficient since 2011, and the number of days that mental and physical health was not good, which is significant on a 95% confidence level. The coefficients are respectively -1.11 and -5.02. This model gives the indication that when the income inequality increased since 2011, the number of days that mental and physical health was not good, decreased. Looking at the change from 2006, there is a positive relationship between this change and the number of days that mental health was not good, which is significant on a 95% confidence interval. The positive coefficient (9.41) indicates that there are more days that mental health was not good, when the Gini Coefficient increased since 2006. With regards to the number of days that physical health was not good, there is no significant relation with the change in the Gini Coefficient since 2006. The positive relation between the change in income inequality since 2006 and the number of days that mental health was not good, is in line with the expectations of the theoretical framework, as described in section 2.4. In the theoretical framework it is mentioned that authors, such as Wilkinson and Pickett (2010) and Kawachi and Kennedy (1999) claim that factors such as *job status, limited possibilities, social capital, stress, anxiety, frustration, social comparisons* influence mental health which subsequently results in more vulnerability for physical health problems. This has been described as a process-oriented development. In line with this development, the results show that increasing income inequality over ten years results in more days that mental health was not good. For physical health this is not the case, according to the model. Looking at the shorter term, it stands out that increase in income inequality results in less days that mental and physical health were not good. This is the opposite of what would be expected, when one relies on the described mechanisms. Other mechanisms or factors which have an impact on the mental and physical health levels seem to be more determinant on the shorter term.

Tables 11 and 12 summarize all results from sections 4.3.1. to 4.3.4. The coefficients and the standard deviations of the models are shown. When there was significance at a 95% confidence interval, the coefficient and the standard deviation are bold.

Number of Days Mental Health was not Good								
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Coef.	***σ***	***Coef.***	***σ***	***Coef.***	***Σ***	***Coef.***	***Σ***
***State** (ref. cat. California)*								
Alabama	**0.707**	**0.119**	0.134	0.114				
Alaska	**-0.409**	**0.163**	-0.228	0.157				
Arizona	**-0.262**	**0.104**	0.161	0.100				
Arkansas	**0.511**	**0.130**	**0.510**	**0.125**				
Colorado	-0.483	0.097	0.058	0.093				
Connecticut	**-0.504**	**0.104**	0.067	0.100				
Delaware	-0.276	0.143	-0.147	0.137				
District of Columbia	-0.273	0.146	**-0.398**	**0.141**				
Florida	-0.002	0.083	-0.001	0.080				
Georgia	-0.223	0.129	**-0.329**	**0.124**				
Hawaii	**-0.653**	**0.113**	-0.189	0.108				
Idaho	-0.161	0.130	**0.246**	**0.125**				
Illinois	**-0.372**	**0.134**	-0.132	0.128				

Indiana	-0.071	0.104	0.155	0.100				
Iowa	**-0.787**	**0.117**	-0.184	0.112				
Kansas	**-0.659**	**0.102**	**-0.233**	**0.098**				
Kentucky	**0.516**	**0.106**	**0.218**	**0.102**				
Louisiana	**0.295**	**0.130**	0.131	0.125				
Maine	-0.054	0.107	**0.222**	**0.102**				
Maryland	**-0.422**	**0.093**	0.000	0.089				
Massachusetts	0.059	0.112	**0.322**	**0.108**				
Michigan	**0.210**	**0.102**	**0.282**	**0.098**				
Minnesota	**-0.818**	**0.094**	**-0.339**	**0.091**				
Mississippi	0.233	0.132	**-0.300**	**0.126**				
Missouri	0.225	0.118	**0.340**	**0.113**				
Montana	**-0.513**	**0.125**	-0.119	0.120				
Nebraska	**-0.805**	**0.096**	**-0.318**	**0.093**				
Nevada	**0.462**	**0.139**	**0.614**	**0.134**				
New Hampshire	-0.220	0.122	0.221	0.117				
New Jersey	**-0.234**	**0.115**	-0.031	0.111				
New Mexico	0.090	0.124	0.145	0.119				
New York	-0.027	0.084	0.040	0.081				
North Carolina	0.167	0.121	0.074	0.116				
North Dakota	**-1.207**	0.126	**-0.549**	**0.121**				
Ohio	-0.032	0.101	0.132	0.097				
Oklahoma	**0.274**	**0.119**	**0.391**	**0.114**				
Oregon	**0.325**	**0.129**	**0.561**	**0.124**				
Pennsylvania	**0.270**	**0.119**	**0.378**	**0.114**				
Rhode Island	0.221	0.128	**0.301**	**0.124**				
South Carolina	**0.372**	**0.104**	**0.296**	**0.100**				
South Dakota	**-0.988**	**0.126**	**-0.486**	**0.121**				
Tennessee	**0.700**	**0.123**	**0.502**	**0.119**				
Texas	**-0.393**	**0.103**	-0.134	0.099				
Utah	-0.215	0.104	**0.315**	**0.100**				
Vermont	0.034	0.121	**0.387**	**0.116**				
Virginia	**-0.376**	**0.110**	-0.139	0.106				
Washington	**-0.255**	**0.098**	0.154	0.094				
West Virginia	**1.110**	**0.118**	**0.723**	**0.113**				
Wisconsin	**-0.372**	**0.130**	0.059	0.125				
Wyoming	**-0.626**	**0.137**	-0.011	0.131				
Female *(ref. cat. Male)*			**0.911**	**0.023**	**0.914**	**0.023**	**0.915**	**0.023**
Age *(ref. cat. Age 18 to 24)*								
Age 25 to 29			**0.198**	**0.071**	**0.198**	**0.071**	**0.197**	**0.071**
Age 30 to 34			0.083	0.071	0.080	0.071	0.079	0.071
Age 35 to 39			-0.031	0.070	-0.033	0.071	-0.033	0.071
Age 40 to 44			-0.119	0.071	-0.112	0.071	-0.113	0.071
Age 45 to 49			**-0.216**	**0.068**	**-0.213**	**0.068**	**-0.215**	**0.068**
Age 50 to 54			**-0.565**	**0.066**	**-0.565**	**0.066**	**-0.565**	**0.066**
Age 55 to 59			**-0.992**	**0.064**	**-0.998**	**0.064**	**-0.997**	**0.064**

Age 60 to 64			**-1.615**	**0.064**	**-1.613**	**0.065**	**-1.611**	**0.065**
Age 65 to 69			**-2.058**	**0.067**	**-2.056**	**0.067**	**-2.054**	**0.067**
Age 70 to 74			**-2.501**	**0.071**	**-2.504**	**0.071**	**-2.501**	**0.071**
Age 75 to 79			**-2.853**	**0.075**	**-2.858**	**0.075**	**-2.855**	**0.075**
Age 80 or older			**-3.312**	**0.072**	**-3.327**	**0.072**	**-3.323**	**0.072**
Married *(ref. cat. Not Married)*			**-1.141**	**0.023**	**-1.144**	**0.024**	**-1.144**	**0.024**
Employment *(ref. cat. Out of work for 1 year or more)*								
Employed for wages			**-3.786**	**0.080**	**-3.800**	**0.081**	**-3.799**	**0.081**
Self-employed			**-3.611**	**0.086**	**-3.639**	**0.087**	**-3.638**	**0.087**
Out of work for less than 1 year			**-0.867**	**0.109**	**-0.870**	**0.110**	**-0.869**	**0.110**
A homemaker			**-3.105**	**0.092**	**-3.097**	**0.093**	**-3.098**	**0.093**
A student			**-3.145**	**0.109**	**-3.159**	**0.109**	**-3.161**	**0.109**
Retired			**-2.738**	**0.084**	**-2.739**	**0.085**	**-2.740**	**0.085**
Unable to work			**3.874**	**0.087**	**3.910**	**0.088**	**3.910**	**0.088**
Education *(Ref. Cat. Never attended school or only kindergarten)*								
Grades 1 through 8 (Elementary)			**0.789**	**0.302**	**0.798**	**0.302**	**0.803**	**0.302**
Grades 9 through 11 (Some high school)			**1.247**	**0.297**	**1.284**	**0.298**	**1.293**	**0.298**
Grade 12 or GED (High school graduate)			0.532	0.294	0.564	0.294	0.574	0.294
College 1 year to 3 years (Some college or technical school)			**0.716**	**0.294**	**0.739**	**0.295**	**0.751**	**0.295**
College 4 years or more (College graduate)			-0.021	0.294	0.003	0.294	0.015	0.294
Gini-Coefficient					**1.128**	**0.530**	**1.144**	**0.534**
Change Gini since 2011							**-1.111**	**1.993**
Change Gini 2006							**9.407**	**1.839**

Table 11. Overview of model outcomes discussed in sections 4.3.1. to 4.3.4. with regards to mental health.

Number of Days Physical Health was not Good								
	Model 1		Model 2		Model 3		Model 4	
	Coef.	*Σ*	*Coef.*	*σ*	*Coef.*	*Σ*	*Coef.*	*σ*
***State** (ref. cat. California)*								
Alabama	**1.366**	**0.136**	-0.091	0.126				
Alaska	**0.454**	**0.187**	**0.361**	**0.173**				
Arizona	1.003	0.120	**0.250**	**0.111**				
Arkansas	**2.033**	**0.149**	**0.479**	**0.138**				
Colorado	-0.124	0.111	-0.121	0.103				
Connecticut	-0.148	0.120	**-0.286**	**0.111**				
Delaware	-0.023	0.164	**-0.482**	**0.152**				
District of Columbia	**-0.501**	**0.168**	**-0.713**	**0.157**				
Florida	**1.093**	**0.096**	0.105	0.089				
Georgia	**0.660**	**0.149**	-0.236	0.137				
Hawaii	-0.097	0.130	-0.056	0.120				
Idaho	**0.559**	**0.150**	0.184	0.139				
Illinois	**0.402**	**0.154**	0.241	0.142				
Indiana	**0.785**	**0.120**	0.013	0.111				
Iowa	**-0.401**	**0.134**	**-0.503**	**0.124**				
Kansas	**-0.259**	**0.117**	**-0.418**	**0.109**				
Kentucky	**1.479**	**0.122**	**0.338**	**0.113**				
Louisiana	**1.161**	**0.150**	-0.031	0.138				
Maine	**0.443**	**0.123**	-0.132	0.113				
Maryland	-0.086	0.107	**-0.358**	**0.099**				
Massachusetts	0.014	0.129	-0.159	0.120				
Michigan	**0.688**	**0.117**	0.138	0.108				
Minnesota	**-0.568**	**0.108**	**-0.354**	**0.100**				
Mississippi	**0.923**	**0.152**	**-0.542**	**0.140**				
Missouri	**1.361**	**0.135**	**0.478**	**0.125**				
Montana	**0.517**	**0.143**	0.132	0.132				
Nebraska	**-0.323**	**0.111**	**-0.356**	**0.102**				
Nevada	**0.840**	**0.160**	**0.408**	**0.148**				
New Hampshire	0.267	0.140	-0.142	0.129				
New Jersey	**0.355**	**0.133**	0.011	0.123				
New Mexico	**1.160**	**0.143**	**0.379**	**0.132**				
New York	**0.554**	**0.097**	-0.040	0.090				
North Carolina	0.263	0.139	-0.295	0.128				
North Dakota	**-0.521**	**0.145**	**-0.452**	**0.134**				
Ohio	**0.737**	**0.116**	0.002	0.107				
Oklahoma	**1.197**	**0.137**	**0.325**	**0.127**				
Oregon	**0.250**	**0.148**	0.167	0.137				
Pennsylvania	0.267	0.137	0.094	0.126				
Rhode Island	**0.580**	**0.148**	-0.041	0.137				
South Carolina	**1.114**	**0.119**	0.000	0.110				
South Dakota	**-0.070**	**0.145**	-0.182	0.133				
Tennessee	**1.610**	**0.142**	**0.574**	**0.132**				
Texas	**0.553**	**0.118**	-0.008	0.109				
Utah	-0.126	0.120	0.216	0.111				

Vermont	0.247	0.139	-0.040	0.128				
Virginia	0.071	0.126	-0.201	0.117				
Washington	**0.310**	**0.112**	0.101	0.104				
West Virginia	**1.914**	**0.135**	**0.629**	**0.125**				
Wisconsin	0.207	0.149	0.081	0.138				
Wyoming	0.327	0.158	-0.007	0.146				
***Female** (ref. cat. Male)*			**0.200**	**0.025**	**0.197**	**0.025**	**0.148**	**0.246**
***Age** (ref. cat. Age 18 to 24)*								
Age 25 to 29			**0.648**	**0.078**	**0.636**	**0.079**	**0.481**	**0.790**
Age 30 to 34			**0.922**	**0.078**	**0.911**	**0.079**	**0.757**	**1.065**
Age 35 to 39			**1.219**	**0.078**	**1.217**	**0.078**	**1.064**	**1.370**
Age 40 to 44			**1.473**	**0.078**	**1.473**	**0.079**	**1.319**	**1.626.904**
Age 45 to 49			**1.789**	**0.075**	**1.789**	**0.076**	**1.640**	**1.937**
Age 50 to 54			**1.990**	**0.073**	**1.980**	**0.073**	**1.837**	**2.123**
Age 55 to 59			**2.039**	**0.071**	**2.023**	**0.071**	**1.883**	**2.163**
Age 60 to 64			**1.779**	**0.071**	**1.765**	**0.071**	**1.626**	**1.906**
Age 65 to 69			**1.750**	**0.074**	**1.735**	**0.074**	**1.591**	**1.882**
Age 70 to 74			**1.835**	**0.078**	**1.820**	**0.078**	**1.667**	**1.974**
Age 75 to 79			**2.067**	**0.083**	**2.056**	**0.083**	**1.895**	**2.220**
Age 80 or older			**2.133**	**0.080**	**2.106**	**0.080**	**1.950**	**2.266**
***Married** (ref. cat. Not Married)*			**-0.706**	**0.026**	**-0.702**	**0.026**	**-0.753**	**-0.650**
***Employment** (ref. cat. Out of work for 1 year or more)*								
Employed for wages			**-4.357**	**0.088**	**-4.410**	**0.089**	**-4.585**	**-4.235**
Self-employed			**-4.249**	**0.096**	**-4.301**	**0.096**	**-4.489**	**-4.111**
Out of work for less than 1 year			**-1.946**	**0.121**	**-1.965**	**0.122**	**-2.204**	**-1.725**
A homemaker			**-3.046**	**0.102**	**-3.055**	**0.102**	**-3.256**	**-2.855**
A student			**-3.761**	**0.120**	**-3.810**	**0.121**	**-4.048**	**-3.573**
Retired			**-2.311**	**0.093**	**-2.336**	**0.094**	**-2.520**	**-2.152**
Unable to work			**8.618**	**0.097**	**8.630**	**0.098**	**8.439**	**8.821**
***Education** (Ref. Cat. Never attended school or only kindergarten)*								
Grades 1 through 8 (Elementary)			0.616	0.337	0.640	0.337	-0.019	1.304
Grades 9 through 11 (Some high school)			0.545	0.332	0.570	0.332	-0.077	1.226

Grade 12 or GED (High school graduate)			-0.326	0.328	-0.303	0.329	-0.942	0.346
College 1 year to 3 years (Some college or technical school)			-0.278	0.328	-0.256	0.329	-0.894	0.394
College 4 years or more (College graduate)			**-1.267**	**0.328**	**-1.264**	**0.329**	**-1.902**	**-0.614**
Gini-Coefficient					**1.895**	**0.587**	**1.943**	**0.592**
Change Gini since 2011							**-5.017**	**2.208**
Change Gini 2006							3.030	2.038

Table 12. Overview of model outcomes discussed in sections 4.3.1. to 4.3.4. with regards to physical health.

Another table has been shown which only shows the significant effects on the number of days that mental or physical health was not good, as it appears in the above analyses. The direction of the relationship is shown by a '+', in the case of a positive relationship and '-', in the case of a negative relationship.

List of Variables That Have Significant Positive (+) Or Negative (-) Effect On Number Of Days That Mental Health Or Physical Health Was Not Good								
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Ment.	*Phys.*	*Ment.*	*Phys.*	*Ment.*	*Phys.*	*Ment.*	*Phys.*
***State** (ref. cat. California)*								
Alabama	+	+		+				
Alaska	-	+						
Arizona	-			+				
Arkansas	+	+	+	+				
Connecticut	-			-				
Delaware				-				
District of Columbia		-	-	-				
Florida		+						
Georgia		+	-					
Hawaii	-							
Idaho		+	+					
Illinois	-	+						
Indiana		+						
Iowa	-	-		-				
Kansas	-	-	-	-				
Kentucky	+	+	+	+				
Louisiana	+	+						
Maine		+	+					
Maryland	-			-				
Massachusetts			+					
Michigan	+	+	+					
Minnesota	-	-	-	-				

Mississippi		+	-	-				
Missouri		+	+	+				
Montana	-	+						
Nebraska	-	-	-	-				
Nevada	+	+	+	+				
New Jersey	-	+						
New Mexico		+		+				
New York		+						
North Dakota	+	-	-	-				
Ohio		+						
Oklahoma	+	+	+	+				
Oregon	+	+	+					
Pennsylvania	+		+					
Rhode Island		+	+					
South Carolina	+	+	+					
South Dakota	-	-	-					
Tennessee	+	+	+	+				
Texas	-	+						
Utah			+					
Vermont			+					
Virginia	-							
Washington	-	+						
West Virginia	+	+	+	+				
Wisconsin	-							
Wyoming	-							
Female *(ref. cat. Male)*			+	+	+	+	+	+
Age *(ref. cat. Age 18 to 24)*								
Age 25 to 29			+	+	+	+	+	+
Age 30 to 34				+		+		+
Age 35 to 39				+		+		+
Age 40 to 44				+		+		+
Age 45 to 49			-	+	-	+	-	+
Age 50 to 54			-	+	-	+	-	+
Age 55 to 59			-	+	-	+	-	+
Age 60 to 64			-	+	-	+	-	+
Age 65 to 69			-	+	-	+	-	+
Age 70 to 74			-	+	-	+	-	+
Age 75 to 79			-	+	-	+	-	+
Age 80 or older			--	+	-	+	-	+
Married *(ref. cat. Not Married)*			-	-	-	-	-	-
Employment *(ref. cat. Out of work for 1 year or more)*								

Employed for wages			-	-	-	-	-	-
Self-employed			-	-	-	-	-	-
Out of work for less than 1 year			-	-	-	-	-	-
A homemaker			-	-	-	-	-	-
A student			-	-	-	-	-	-
Retired			-	-	-	-	-	-
Unable to work			+	+	+	+	+	+
Education *(Ref. Cat. Never attended school or only kindergarten)*								
Grades 1 through 8 (Elementary)			+		+		+	
Grades 9 through 11 (Some high school)			+		+		+	
College 1 year to 3 years (Some college or technical school)			+		+		+	
College 4 years or more (College graduate)				-		-		-
Gini-Coefficient					+	+	+	+
Change Gini since 2011							-	-
Change Gini 2006							+	

Table 13. Overview of variables that have a significant effect on number of days that mental health or physical health was not good

4.3.5. Spillover Effect Mental Health

As mentioned, the main objective of this research is to find out if a *spillover effect* exists to a certain extent. Several analyses have been conducted to get insight in this phenomenon. *Income* has been taken into account in the following analysis, by using interaction variables. These interaction variables contain the binary dummy income variables (table 2) and the Gini Coefficient. This interaction variable provides an indication about the well-being of an individual with a relatively high income, living in an state where income inequality is relatively high or low: this is in line with the conceptualization of the spillover effect, which implies that well-being levels of people with relatively high incomes are lower in areas where income inequality is relatively high, compared to people with the same income at a place where income inequality is lower. The six tables in appendix 11 show the outcomes of the regression models where *number of days mental health was not good* is used as dependent variable. The models have been represented by equation 3.7.

All interaction variables are significant on a 95% confidence level. For all income levels (higher than 15,000 to higher than 75,000) there is a positive relation between the interaction variable and the dependent variable. The outcomes are in line with the concept of the *spillover effect*. The model implies that if the income is higher than 15,000, 20,000, 25,000, 35,000, 50,000 or 75,000, the number of days mental health was not good depends on the level of income inequality, expressed by the Gini-Coefficient. If the Gini-Coefficient is higher, there is a higher number of days that mental health was not good for people with these incomes.

The coefficient for the Gini-Coefficient, turns negative when the interaction variables have been added to the model, and is significant on a 95% confidence level, for the first four models. This would imply that when income inequality increases, the number of days mental health was not good decreases, at first glance. However, the Gini-Coefficient cannot be interpreted on its own when an interaction variable is added to the model. The model of equation 3.7. is shown below and the coefficients where the Gini-Coefficient is taken into account are in bold:

$$Y = \beta 0 + \beta 1_{\text{state}} + \beta 2_{\text{age}} + \beta 3_{\text{maritalstatus}} + \beta 4_{\text{sex}} + \beta 5_{\text{employment}} + \beta 6_{\text{education}} + \boldsymbol{\beta 7}_{\textbf{Gini-coefficient}} + \boldsymbol{\beta 8}_{\textbf{(IncomeHigher * Gini-Coefficient)}} + R$$

As shown by the equation, both the coefficient of β7, as the coefficient of β8, take into account the Gini-Coefficient. The relationship between income inequality and *number of days mental health was not good* has been influenced by the binary dummy variable, due to the introduction of the interaction variable. When the Gini-Coefficient increases or decreases, it matters if someone has a lower or higher income than the level of the particular income level of the binary dummy variable, with regards to the influence on the *number of days mental health was not good*. In the case someone has a higher income than the income level which has been taken into account in the binary dummy variable *IncomeHigher,* the variable has a value of 1. This is relevant, since this research focuses on the *spillover effect*, which implies that people with higher incomes are also affected by income inequality. Therefore, the influence of income inequality, in the case if someone has a higher income than, for example 15,000, has been calculated by the coefficient of β7, plus the coefficient of β8 multiplied by 1. Table 39 (appendix 11), which focuses on the income dummy variable, which takes into account the individuals with an income higher of lower than 15,000, shows that the Gini-Coefficient-variable has a coefficient of -7.26 and that the interaction variable has a coefficient of 9.07. Assuming that an individual has an income higher than 15,000, the interaction variable has to be multiplied by 1. This value, plus the coefficient of the Gini-Coefficient-variable, which is -7.26, shows the influence of income inequality, for an individual with an income higher than 15,000, on the number of days that mental health was not good. In this case, this value has a factor of 1.81.

These calculations have been performed for all income levels where both the interaction variable, and the Gini-Coefficient-variables are significant on a 95% confidence level.

The calculations below show how the Gini Coefficients should be interpreted for the first 4 income groups, where both the Gini-Coefficient-variable as the interaction variable are significant on a 95% confidence level. These calculations show the effect of the Gini-coefficient on the number of days mental health was not good, represented by *Y* in equation 3.7., where it has been assumed that an individual has a higher income than that particular level.

Income higher than 15,000: $\frac{\delta y}{\delta Gini}$= -7.26 + 9.07*1= **1.81**

Income higher than 20,000: $\frac{\delta y}{\delta Gini}$= -7.12 + 9.46*1= **2.34**

Income higher than 25,000: $\frac{\delta y}{\delta Gini}$= -5.50+ 8.32*1= **2.82**

Income higher than 35,000: $\frac{\delta y}{\delta Gini}$= -3.41+ 6.52*1= **3.11**

In the models where the interaction variables contain the variables with the income levels of 50,000 and 75,000, the Gini-Coefficients are not significant on a 95% confidence level, which makes it that this interaction variable cannot be interpreted in the same way as the variables in the calculations above. However, the interaction variables are significant on a 95% confidence level, which suggests that the Gini-Coefficient has influence on the number of days that mental health was not good of people with an income higher than 50,000 and 75,000. The four calculations above show that there is a positive effect of the Gini-Coefficient on the number of days mental health was not good, when the income level is higher than 15,000, 20,000, 25,000 or 35,000. As mentioned, this is in line with the concept of the *spillover effect*. In section 2.5., the definition of the spillover effect and the mechanisms that result in this spillover effect have been explained. For example, Lynch et al. (2004), Kawachi and Kennedy (1997), Wilkinson and Pickett (2010) and Kondo et al. (2010) claim that income inequality affects the whole population, and not only the poor. With regards to mental health, Wilkinson and Pickett, for example, mention that rates of mental illness are five times higher in the most unequal societies. Kawachi and Kennedy mention that high income inequality results in lower social capital and lower civic trust and more crime, which makes it less comfortable for people of all income groups to live in that particular place. In line with this, Daly et al. (1998) mention that antisocial behavior and limited access to facilities increase in places with a high level of income inequality. Furthermore, it has been explained in sections 2.4. and 2.5. by for example Layte (2012) and Kondo et al. (2010), that income inequality results in more status anxiety and social comparisons, which affect the levels of stress and frustration, across different income levels. This results in lower levels of mental health for the whole society. Layte (2012) states that more social trust is associated with 'collective efficacy', which means that neighbours and relative strangers are willing to offer social support or prevent abnormal behaviour. This will result in an increase in the overall level of quality of life. Therefore, societies with low levels of community life and trust are also the societies with a relatively low level of mental health. The mechanisms, as explained above, result in higher overall levels of mental health. The outcomes of the models shown in appendix 11 confirm these findings. There has been found a significant relationship between all interaction variables and number of days mental health was not good. The number of days that mental health was not good will increase when income inequality is higher, across all income groups, according to the models used in this analysis. Across all income groups, it has been shown that income inequality affects the mental well-being which confirms the existence of a spillover effect with regards to mental health.

4.3.6. Spillover Effect Physical Health

The same analyses have been conducted as the analyses of section 4.3.3. In this section, however, *number of days physical health was not good* is used as a dependent variable. The outcomes of these models have been shown in appendix 12.

The first 5 interaction variables in the first four models are significant on a 95% confidence level. For these interaction variables (higher than 15,000 to higher than 50,000), there is a positive relation between the interaction variable and the dependent variable. These outcomes are in line with the concept of the *spillover effect*. The model suggests that if the income is higher than 15,000, 20,000, 25,000, 35,000 and 50,000, the number of days physical health was not good depends on the level of income inequality, expressed by the Gini-Coefficient. If the Gini-Coefficient is higher, there are more days that physical health was not good for people with these incomes. For the highest incomes (higher than 75.000), this pattern is absent.

Similar to the model where *number of days mental health was not good* has been used as dependent variable, the coefficient for the Gini-Coefficient turns negative when interaction variables are added to the model, and are significant on a 95% confidence level, for the first three models. At first sight, this would imply that when income inequality increases, the number of days physical health was not good, decrease. However, as already explained in the previous section, the Gini-Coefficient cannot be interpreted on its own when an interaction variable is added to the model. When the Gini-Coefficient increases or decreases, it matters if someone has a lower or higher income than the level of the particular income level of the binary dummy variable, with regards to the influence on the *number of days physical health was not good*. The calculations, as explained in the previous section 4.3.5., have also been performed for the analyses where the number of days *physical health was not good* is used as dependent variable. The calculations below show how the Gini Coefficients should be interpreted for the first 3 income groups. These calculations show the influence of the Gini-coefficient on the number of days physical health was not good, represented by *Y* in equation 3.7., where it has been assumed that an individual has a higher income than that particular level.

Income higher than 15,000: $\frac{\delta y}{\delta Gini}$= -10.83+ 13.39*1= **2.56**

Income higher than 20,000: $\frac{\delta y}{\delta Gini}$= -7.53 + 10.27*1= **2.74**

Income higher than 25,000: $\frac{\delta y}{\delta Gini}$= -4.79+ 7.68*1= **2.89**

In the models where the interaction variables contain of the variable with the income levels of 35,000 and 50,000, the Gini-Coefficient is not significant on a 95% confidence level, which makes that this interaction variable cannot be interpreted in the same way as the variables in the calculations above. However, the interaction variable is significant on a 95% confidence level, which suggests that the Gini-Coefficient has influence on the number of days that physical health was not good of people with an income higher than 35,000 or 50,000. The four calculations above show that there is a positive effect of the Gini-Coefficient on the number of days mental health was not good, when the income level is higher than 15,000, 20,000 or 25,000. As mentioned, this is in line with the concept of the spillover effect. In contrast to the previous section 4.3.5. which focused on mental health, this section looks at the spillover effect with regards to physical health. Kawachi and Kennedy (1997), Wilkinson and Pickett (2010) and Lynch et al. (2004) argue that income inequality affects the population health and the mortality rate of the whole society. Wilksinon and Pickett (2010) and Kawachi and Kennedy (1999) explain that levels of mental health are a *determinant* for physical health levels, as explained in section 2.4.3. This indicates that many arguments which describe the spillover effect with regards to mental health also apply to physical health to a certain extent. However, some arguments which explain the spillover effect, as analyzed in this analysis, have been highlighted in this section. Wilkinson (1997) indicates that there is a positive link between cohesion and population health. As explained in previous sections, it is reasonable that income inequality influences the social cohesion. Wilkinson explains that the social environment is crucial for people's psychological welfare and the prevalence of chronic stress in a population. It has been assumed that income inequality leads to less cohesion in a society, which can lead to increasing stress and frustration, resulting in decreasing physical health. Even more so, *status* and *social comparisons* are mechanisms that explain the relationship between income inequality and health level across the whole society. Kondo et al. (2009) assume that status anxiety and social comparisons leads to psychological stress which is harmful for the entire society, consisting of people from different income groups. This has also been pointed out by Layte (2012), who claims that status anxiety is mainly associated with unequal societies. These societies suffer more mental health problems as a result of the social anxiety. Besides, it has been explained in section 2.5 that income inequality results in deterioration of public facilities and education systems and erosion of support for public schools, which negatively affects health levels in a particular place (Kawachi and Kenndy, 1997, Daly et al. 1998). These are possible mechanisms that explain how income inequality results in lower health levels for the whole society. The spillover effect comes forward to a lesser extent when the *number of days physical health was not good* has been used as a dependent variable, instead of *number of days mental health was not good*. There appears not to be a spillover effect for the highest income groups, according to the models in appendix 12. According to the models used in this research, the spillover effect on physical health is less strong than the spillover effect on mental health. However, for all other income groups, except for the highest income group, it stands out that when income inequality increases, the number of days physical health was not good also increases. Across different income groups, it has been shown that income inequality affects the physical well-being which partly confirms the existence of a spillover effect.

Tables 14 and 15 summarize all results from sections 4.3.1. to 4.3.4. The coefficients and the standard deviations of the models have been shown. When there was significance at a 95% confidence interval, the coefficient and the standard deviation are bold.

Number of Days Mental Health was not Good												
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	*σ*	*Coef.*	*Σ*	*Coef.*	*σ*	*Coef.*	*σ*	*Coef.*	*σ*	*Coef.*	*σ*
***Female** (ref. cat. Male)*	0.931	0.025	0.914	0.025	0.896	0.025	0.893	0.025	0.902	0.025	0.918	0.025
***Age** (ref. cat. Age 18 to 24)*												
Age 25 to 29	0.103	0.079	0.097	0.079	0.090	0.079	0.065	0.079	0.039	0.079	0.034	0.079
Age 30 to 34	-0.049	0.078	-0.057	0.078	-0.052	0.078	-0.047	0.078	-0.044	0.078	-0.055	0.078
Age 35 to 39	-0.139	0.078	-0.141	0.078	-0.129	0.078	-0.112	0.078	-0.094	0.078	-0.095	0.078
Age 40 to 44	-0.230	0.078	-0.230	0.078	-0.210	0.078	-0.185	0.078	-0.159	0.078	-0.154	0.078
Age 45 to 49	-0.373	0.076	-0.363	0.076	-0.333	0.076	-0.301	0.076	-0.280	0.076	-0.282	0.076
Age 50 to 54	-0.690	0.073	-0.674	0.073	-0.640	0.073	-0.614	0.073	-0.592	0.073	-0.604	0.073
Age 55 to 59	-1.145	0.072	-1.129	0.072	-1.092	0.072	-1.069	0.072	-1.057	0.072	-1.079	0.072
Age 60 to 64	-1.688	0.072	-1.679	0.072	-1.650	0.072	-1.639	0.072	-1.641	0.072	-1.664	0.072
Age 65 to 69	-2.138	0.075	-2.133	0.075	-2.118	0.075	-2.124	0.075	-2.137	0.075	-2.151	0.075
Age 70 to 74	-2.536	0.079	-2.531	0.079	-2.533	0.079	-2.549	0.079	-2.564	0.079	-2.567	0.079
Age 75 to 79	-2.943	0.084	-2.949	0.084	-2.958	0.084	-2.990	0.084	-3.000	0.084	-2.990	0.084
Age 80 or older	-3.368	0.082	-3.400	0.082	-3.426	0.082	-3.461	0.082	-3.453	0.082	-3.416	0.082
***Married** (ref. cat. Not Married)*	-0.998	0.026	-0.924	0.026	-0.862	0.026	-0.846	0.027	-0.862	0.027	-0.948	0.026
***Employment** (ref. cat. Out of work for 1 year or more)*												
Employed for wages	-3.626	0.090	-3.561	0.090	-3.533	0.090	-3.599	0.090	-3.699	0.089	-3.822	0.089
Self-employed	-3.494	0.096	-3.448	0.096	-3.437	0.096	-3.495	0.096	-3.585	0.096	-3.673	0.096
Out of work for less than 1 year	-0.968	0.122	-0.972	0.122	-0.995	0.122	-1.026	0.122	-1.068	0.122	-1.102	0.122
A homemaker	-2.974	0.103	-2.945	0.103	-2.944	0.103	-3.002	0.103	-3.080	0.103	-3.154	0.103
A student	-3.097	0.123	-3.058	0.123	-3.033	0.123	-3.043	0.123	-3.078	0.123	-3.141	0.123
Retired	-2.643	0.094	-2.610	0.094	-2.617	0.094	-2.688	0.094	-2.792	0.094	-2.882	0.094
Unable to work	3.793	0.097	3.775	0.097	3.779	0.097	3.804	0.097	3.818	0.097	3.836	0.097
***Education** (Ref. Cat. Never attended school or only kindergarten)*												
Grades 1 through 8 (Elementary)	0.723	0.360	0.717	0.360	0.746	0.360	0.778	0.360	0.776	0.360	0.786	0.360
Grades 9 through 11 (Some high school)	1.220	0.355	1.235	0.355	1.266	0.354	1.281	0.354	1.244	0.355	1.217	0.355
Grade 12 or GED (High school graduate)	0.637	0.351	0.708	0.351	0.749	0.351	0.722	0.351	0.609	0.351	0.519	0.351
College 1 year to 3 years (Some college or technical school)	0.856	0.351	0.967	0.351	1.047	0.351	1.026	0.351	0.897	0.351	0.759	0.351

College 4 years or more (College graduate)	0.160	0.351	0.310	0.351	0.452	0.351	0.482	0.351	0.389	0.351	0.222	0.351
Gini-Coefficient	**-7.255**	**1.885**	**-7.121**	**1.412**	**-5.502**	**1.134**	**-3.414**	**0.952**	-1.428	0.806	0.235	0.699
Income higher than 15,000 *(ref. cat. lower than 15,000)*	**-5.661**	**0.932**										
Income higher than 20,000 *(ref. cat. lower than 20,000)*			**-5.743**	**0.727**								
Income higher than 25,000 *(ref. cat. lower than 25,000)*					**-5.165**	**0.616**						
Income higher than 35,000 *(ref. cat. lower than 35,000)*							**-4.177**	**0.558**				
Income higher than 50,000 *(ref. cat. lower than 50,000)*									**-3.262**	**0.534**		
Income higher than 75,000 *(ref. cat. lower than 75,000)*											**-2.300**	**0.565**
Interaction variable												
Higher than 15,000xGini	**9.072**	**1.977**										
Higher than 20,000xGini			**9.463**	**1.543**								
Higher than 25,000xGini					**8.322**	**1.311**						
Higher than 35,000xGini							**6.516**	**1.187**				
Higher than 50,000xGini									**4.789**	**1.138**		
Higher than 75,000xGini											**3.076**	**1.206**

Table 14. Overview of model outcomes discussed in sections 4.3.5. to 4.3.6. with regards to mental health.

Number of Days Physical Health was not Good												
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	*σ*	*Coef.*	*Σ*	*Coef.*	*σ*	*Coef.*	*σ*	*Coef.*	*σ*	*Coef.*	*σ*
Female *(ref. cat. Male)*	0.208	0.027	0.183	0.027	0.158	0.027	0.150	0.027	0.167	0.027	0.189	0.027
Age *(ref. cat. Age 18 to 24)*												
Age 25 to 29	0.557	0.087	0.545	0.086	0.535	0.086	0.498	0.086	0.471	0.086	0.470	0.087
Age 30 to 34	0.807	0.086	0.792	0.086	0.797	0.086	0.799	0.086	0.804	0.086	0.793	0.086
Age 35 to 39	1.093	0.085	1.084	0.085	1.097	0.085	1.116	0.085	1.139	0.085	1.139	0.085
Age 40 to 44	1.347	0.086	1.339	0.086	1.363	0.086	1.394	0.086	1.424	0.086	1.430	0.086
Age 45 to 49	1.630	0.083	1.637	0.083	1.673	0.083	1.713	0.083	1.735	0.083	1.730	0.083
Age 50 to 54	1.866	0.080	1.879	0.080	1.921	0.080	1.955	0.080	1.979	0.080	1.962	0.080
Age 55 to 59	1.884	0.079	1.899	0.079	1.944	0.079	1.975	0.079	1.987	0.079	1.958	0.079
Age 60 to 64	1.641	0.079	1.649	0.079	1.685	0.079	1.700	0.079	1.694	0.079	1.666	0.079
Age 65 to 69	1.625	0.082	1.630	0.082	1.648	0.082	1.640	0.082	1.624	0.082	1.608	0.082
Age 70 to 74	1.782	0.087	1.788	0.087	1.786	0.087	1.764	0.087	1.746	0.087	1.744	0.087
Age 75 to 79	1.991	0.092	1.984	0.092	1.973	0.092	1.930	0.092	1.920	0.092	1.934	0.092
Age 80 or older	2.093	0.091	2.056	0.091	2.023	0.090	1.972	0.090	1.987	0.091	2.036	0.091
Married *(ref. cat. Not Married)*	-0.548	0.028	-0.434	0.029	-0.347	0.029	-0.307	0.029	-0.353	0.029	-0.468	0.029
Employment *(ref. cat. Out of work for 1 year or more)*												
Employed for wages	-4.232	0.099	-4.092	0.099	-4.038	0.099	-4.095	0.098	-4.258	0.098	-4.419	0.098
Self-employed	-4.160	0.106	-4.050	0.106	-4.020	0.106	-4.071	0.105	-4.215	0.105	-4.332	0.105
Out of work for less than 1 year	-1.943	0.134	-1.921	0.134	-1.942	0.133	-1.974	0.133	-2.038	0.133	-2.080	0.134
A homemaker	-2.977	0.113	-2.896	0.113	-2.882	0.113	-2.938	0.113	-3.061	0.113	-3.158	0.113
A student	-3.805	0.135	-3.727	0.135	-3.684	0.135	-3.681	0.135	-3.749	0.135	-3.834	0.135
Retired	-2.211	0.103	-2.122	0.103	-2.116	0.103	-2.189	0.103	-2.344	0.103	-2.459	0.103
Unable to work	8.586	0.107	8.554	0.107	8.555	0.107	8.584	0.107	8.605	0.107	8.629	0.107
Education *(Ref. Cat. Never attended school or only kindergarten)*												
Grades 1 through 8 (Elementary)	0.801	0.397	0.784	0.396	0.832	0.396	0.876	0.396	0.869	0.396	0.872	0.397
Grades 9 through 11 (Some high school)	0.728	0.391	0.755	0.391	0.814	0.390	0.844	0.390	0.782	0.391	0.737	0.391
Grade 12 or GED (High school graduate)	0.032	0.387	0.156	0.387	0.239	0.387	0.229	0.387	0.056	0.387	-0.071	0.387
College 1 year to 3 years (Some college or technical school)	0.130	0.387	0.311	0.387	0.446	0.387	0.455	0.387	0.249	0.387	0.058	0.387

College 4 years or more (College graduate)	**-0.838**	**0.387**	-0.603	0.387	-0.386	0.387	-0.302	0.387	-0.479	0.387	-0.715	0.387
Gini-Coefficient	**-10.829**	**2.073.022**	**-7.530**	**1.552**	**-4.794**	**1.246**	**-1.667**	**1.046**	0.004	0.885	1.329	0.768
Income higher than 15,000 *(ref. cat. lower than 15,000)*	**-7.792**	**1.025**										
Income higher than 20,000 *(ref. cat. lower than 20,000)*			**-6.418**	**0.798**								
Income higher than 25,000 *(ref. cat. lower than 25,000)*					**-5.199**	**0.677**						
Income higher than 35,000 *(ref. cat. lower than 35,000)*							**-3.432**	**0.612**				
Income higher than 50,000 *(ref. cat. lower than 50,000)*									**-2.463**	**0.585**		
Income higher than 75,000 *(ref. cat. lower than 75,000)*											**-1.469**	**0.619**
Interaction variable												
Higher than 15,000xGini	**13.394**	**2.173**										
Higher than 20,000xGini			**10.273**	**1.694**								
Higher than 25,000xGini					**7.684**	**1.439**						
Higher than 35,000xGini							**4.137**	**1.303**				
Higher than 50,000xGini									**2.561**	**1.249**		
Higher than 75,000xGini											0.950	1.322

Table 15. Overview of model outcomes discussed in sections 4.3.1. to 4.3.4. with regards to physical health.

The table below only shows the significant effects on the number of days that mental or physical health was not good, as it appears in the above analyzes. The direction of the relationship is shown by a '+', in the case of a positive relationship and '-', in the case of a negative relationship.

List of Variables That Have Significant Positive (+) Or Negative (-) Effect On Number Of Days That Mental Health Or Physical Health Was Not Good												
	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**	
	Ment.	*Phys.*	*Ment.*	*Phys.*	*Ment.*	*Phys.*	*Ment.*	*Phys.*	*Ment.*	*Phys.*	*Ment.*	*Phys.*
***Female** (ref. cat. Male)*	+	+	+	+	+	+	+	+	+	+	+	+
***Age** (ref. cat. Age 18 to 24)*												
Age 25 to 29		+		+		+		+		+		+
Age 30 to 34		+		+		+		+		+		+
Age 35 to 39		+		+		+		+		+		+
Age 40 to 44	-	+	-	+	-	+	-	+	-	+	-	+
Age 45 to 49	-	+	-	+	-	+	-	+	-	+	-	+
Age 50 to 54	-	+	-	+	-	+	-	+	-	+	-	+
Age 55 to 59	-	+	-	+	-	+	-	+	-	+	-	+
Age 60 to 64	-	+	-	+	-	+	-	+	-	+	-	+
Age 65 to 69	-	+	-	+	-	+	-	+	-	+	-	+
Age 70 to 74	-	+	-	+	-	+	-	+	-	+	-	+
Age 75 to 79	-	+	-	+	-	+	-	+	-	+	-	+
Age 80 or older	-	+	-	+	-		-	+	-	+	-	+
***Married** (ref. cat. Not Married)*	-	-	-	-	-	-	-	-	-	-	-	-
***Employment** (ref. cat. Out of work for 1 year or more)*												
Employed for wages	-	-	-	-	-	-	-	-	-	-	-	-
Self-employed	-	-	-	-	-	-	-	-	-	-	-	-
Out of work for less than 1 year	-	-	-	-	-	-	-	-	-	-	-	-
A homemaker	-	-	-	-	-	-	-	-	-	-	-	-
A student	-	-	-	-	-	-	-	-	-	-	-	-
Retired	-	-	-	-	-	-	-	-	-	-	-	-
Unable to work	+	+	+	+	+	+	+	+	+	+	+	+

Education *(Ref. Cat. Never attended school or only kindergarten)*												
Grades 1 through 8 (Elementary)	+	+	+	+	+	+	+	+	+	+	+	+
Grades 9 through 11 (Some high school)	+		+		+	+	+	+	+	+	+	
Grade 12 or GED (High school graduate)			+		+		+					
College 1 year to 3 years (Some college or technical school)	+		+		+		+		+		+	
College 4 years or more (College graduate)		-										
Gini-Coefficient	-	-	-	-	-	-	-	-				
Income higher than 15,000 *(ref. cat. lower than 15,000)*	-	-										
Income higher than 20,000 *(ref. cat. lower than20,000)*			-	-								
Income higher than 25,000 *(ref. cat. lower than 25,000)*					-	-						
Income higher than 35,000 *(ref. cat. lower than 35,000)*							-	-				
Income higher than 50,000 *(ref. cat. lower than 50,000)*									-	-		
Income higher than 75,000 *(ref. cat. lower than 75,000)*											-	-

Interaction variable												
Higher than 15,000xGini	+	+										
Higher than 20,000xGini			+	+								
Higher than 25,000xGini					+	+						
Higher than 35,000xGini							+	+				
Higher than 50,000xGini									+	+		
Higher than 75,000xGini											+	

Table 16. Overview of variables that have a significant effect on number Of days that mental health or physical health was not good

5. Discussion and Concluding Comments

The research presented here demonstrates that there is a *spillover effect* of income inequality on society at large. A spillover effect means that not only the lowest incomes are confronted by income inequality. The research shows that also people with higher incomes, living in a state with higher income inequality, have lower self-assessed mental and physical health than people living in a state with less income inequality. The main research question is: "*To what extent does a spillover effect, caused by income inequality, exist in the United States?".*

The first step of this research has been to get insight in the level of income inequality within and between different geographical scale levels, in order to answer the research question: *What is the degree of income inequality between and within different geographical scale levels in Orange County, California and the United States?.* Section 4.1. provides an overview of Gini-Coefficients of cities in Orange County, counties in California and American States, which are also the geographical scale levels this research is focussed on. It stands out that within Orange County, especially the cities of Irvine and Newport Beach have a relatively high level of income inequality. Within California, the Gini-Coefficient of Orange County does not stand out and mainly counties with large cities, such as Los Angeles and San Francisco have a relatively high level of income inequality. Within the United States, California has the fourth highest Gini-Coefficient. Only Connecticut, Louisiana and New York have a higher Gini-Coefficient. States with the lowest Gini-coefficients are Alaska, New Hampshire, Utah and Wyoming.

A number of authors show evidence that a relationship between income inequality and well-being, mental health and physical health exists. These authors, such as Wilkinson and Pickett (2010), Kawachi and Kennedy (1999), Sturm and Gresenz (2002) and Fiscella and Franks (2000), show that when income inequality in a country or state is higher, the mental or physical health level is lower in this country or state. Fiscella and Franks (2000), for example, mention that income inequality is associated with depressive symptoms, which then results in a lower self-reported health and higher mortality. According to a number of theories, which have been discussed in section 2.4.2. and 2.4.3., income inequality results in higher levels of stress, frustration and anxiety and lower levels of social cohesion and social capital, which in return leads to lower levels of mental and physical health For example, Kawachi and Kennedy (1999) suggest that income inequality is associated with disinvestment in human capital, erosion of social capital and social comparisons. In contrast to these studies with regards to the relationship between income inequality, and well-being and health, the research presented here focuses on which geographical scale level this relationship occurs and to what extent the so-called spillover effect exists. Therefore, this study adds a spatial component to this relationship and makes a comparison between different income levels.

The socio-economic and psychological consequences of income inequality, as described above, come forward at the country-level, where income inequality at the state-level has been taken into account. At the state-level and the county-level, where income inequality at the county-level and city-level has been taken into account respectively, these consequences do not stand out. In order to answer the research question: *"What are the socio-economic and psychosocial consequences of income inequality in the context of Orange County, California and the United States?",* analyses have been conducted which add a spatial component to the relationship between income inequality and well-being and health. This tends to provide insight into on which geographical scale level these relationships between income inequality and mental and physical health appear. A multilevel analysis has been carried out for this analysis. By conducting a multilevel analysis, insight has been obtained in the extent to which a relationship exists between social-economic and psychological indicators and income inequality. On three levels there has been looked at the relationship between self-assessed mental and physical health, and income inequality: at the level of Orange County, California and at the level of United States, where respectively cities, counties and states have been analyzed as contextual factors. The dataset of the 500-cities project has been used for this analysis. As mentioned in section 3.2.2., these data consist of averages at the Census Tract level, which means that the micro-units in the dataset are averages of Census Tracts.

It is striking that only a positive relation between income inequality and 'the average number of people who report that more than 14 days *mental* or *physical health* was not good the 30 days before they completed the survey' comes forward at the country-level where states are taken into account as geographical contextual effect. In the analyses where there has been focused on lower geographical levels, a negative or non-significant relationship between income inequality and 'the average number of people in a who report that more than 14 days *mental* or *physical health* was not good the 30 days before they completed the survey' stands out. Even more so, the effect of the state where people in a Census Tract are living, is stronger when the Gini-Coefficient and other predictors are added to the model. In this case, the influence of the Gini-Coefficient on *mental* and *physical* health, also increases. However at lower geographical levels, the effect of the city or county where people in a Census Tract are living, is weaker when the Gini-Coefficient and other predictors are added to the model. This insight provides an answer to the research question: "*To what extent are the social-economic and psychological consequences of income inequality related to their geographical context?".* The model shows that 'state' as geographical context matters in this relationship, but that lower geographical contexts, such as cities (in Orange County) and counties (in California) matter less, with regards to the relationship, as described above. As mentioned, Kawachi and Kennedy (1999) and Wilkinson and Pickett (2010) explain that *job status, limited possibilities, social capital, stress, anxiety, frustration*, and *social comparisons* are factors that affect mental health which subsequently results in more vulnerability for physical health problems. The described mechanisms would imply that income inequality has an impact on the direct surrounding of a group of people. Based on these mechanisms, one might expect that at a lower geographical level, income inequality has more influence on the mental or physical well-being of people living in a Census Tract. However, the outcomes of the model do not correspond with this assumption. The outcomes imply that other mechanisms or factors have a more important influence on the mental and physical well-being at the level of counties in California and cities in Orange County. It stands out that the positive influence of income inequality on the average deterioration of *mental* and *physical health* in a Census-Tract matters at the country level, which is in line with the evidence shown in 2.4.3. At lower geographical levels, this pattern does not stand out and other mechanisms and factors might play a more important role.

As mentioned, the main focus of this research is on the so-called *spillover effect*, which implies that not only people with lower incomes experience negative outcomes due to income inequality, but also people with higher incomes. Various mechanisms, as described in the theoretical framework, explain this phenomenon. For example, Kawachi and Kennedy (1997) mention that high income inequality results in lower social capital and lower civic trust and more crime, which makes it less comfortable for people of all income groups to live in that particular place. The existence of a spillover effect implies that an equal income distribution is advantageous for the whole society. Lynch et al. (2004), Kondo et al. (2009) and Wilkinson and Pickett (2010) also mention that income inequality affects the *whole* society. Research has been conducted to get insight into this spillover effect. In contrast to the authors mentioned above, this research focuses on the influence of income inequality on mental and physical health levels across different income levels. This kind of analysis provides an indication to what extent people with higher incomes are affected by the level of income inequality in the state where they live. This analysis makes use of the BRFSS-data. In contrast to the

500 Cities Project-dataset, this dataset consists of data with individuals as micro-units and states as only geographical information. The Gini-Coefficients have been considered at the state-level and the influence of the Gini-Coefficients is analyzed on the self-assessed health, expressed in “number of days in a month *mental* and *physical health* was not good”. Tobit regressions have been carried out for this analysis. In line with the outcomes of the Multilevel Analyses and the findings of the authors mentioned above, it stands out that at the country-level, a positive relationship exists between income inequality at the state-level and the “number of days mental and physical health was not good”. To find out to what extent the spillover effect exists, interaction variables are used which consist of the Gini-Coefficient at state level and a dummy variable that shows if an individual earns more than a particular income. This interaction variable shows the influence of income inequality specifically for higher incomes on their self-assessed mental and physical health. A positive relation between the interaction variable and self-assessed mental health stands out for all income levels, except for the highest income category, in the case of *physical health*. This shows that the spillover effect exists to a certain extent. Not only the lowest incomes are confronted by income inequality. The model shows that also people with a higher income, living in a state with higher income inequality, have lower self-assessed mental and physical health than people living in a state with less income inequality. These outcomes are partly in line with the findings of the researchers mentioned above, who claim that income inequality affects the whole society. However, the relationship does not stand out for the highest income group of the society in the case of the relationship between income inequality and self-assessed *physical health*. Still, it could be concluded that, at the level of the United States, considering the income inequality at the state-level, income inequality is not only affecting the mental and physical health of people of the lower income groups, but also that of the higher income groups. This finding confirms the existence of a *spillover-effect* of income inequality on society at large, across different income levels.

Some recommendations for future research come forward, based on the outcomes of this research. As mentioned, a negative relationship between income inequality and the “number of days mental and physical health are not good” exists at the state and county level. This is in contrast to what would be expected based on previous research. Other mechanisms and factors might have influence on the self-assessed health at these lower scale levels. Future research could focus on these mechanisms at lower scale levels. Research could focus on the explanation of this direction in the relationship between income inequality and health. Furthermore, only quantitative methods have been used for this research. More profound insight in the influence of income inequality can be obtained by using qualitative methods, with the focus on the question why income inequality has its consequences and why a spillover effect exists.

Another recommendation for future research could be to focus on the spillover effect at lower geographical levels. In this research the spillover effect has been analysed at the level of the United States. However, at lower geographical levels, such as states, counties and cities, other mechanisms might play an important role, which makes it meaningful to do a similar analysis at these scale levels. When focussing on lower scale levels, *Spatial Microsimulation* or *Spatial Econometrics* might be an interesting technique to get insight into the effects at lower geographical scale levels. Ballas and Clarke (2000) explain that microsimulation models aim at constructing large-scale data sets on the attributes of individuals or households and at getting insight in impact of policy on these micro-units. Spatial econometrics focusses on dependence among observations that are in close geographical proximity, and attempts to find spatial patterns (LeSage, 2008). By using techniques related to spatial microsimulation or spatial econometrics, insight might be gained in phenomena at a macro scale level, such as income inequality and its related redistribution policy at the state-, county-, city- or neighbourhood-level and the impact of it on ‘micro-units’ as individuals.

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Appendix 1. Histograms

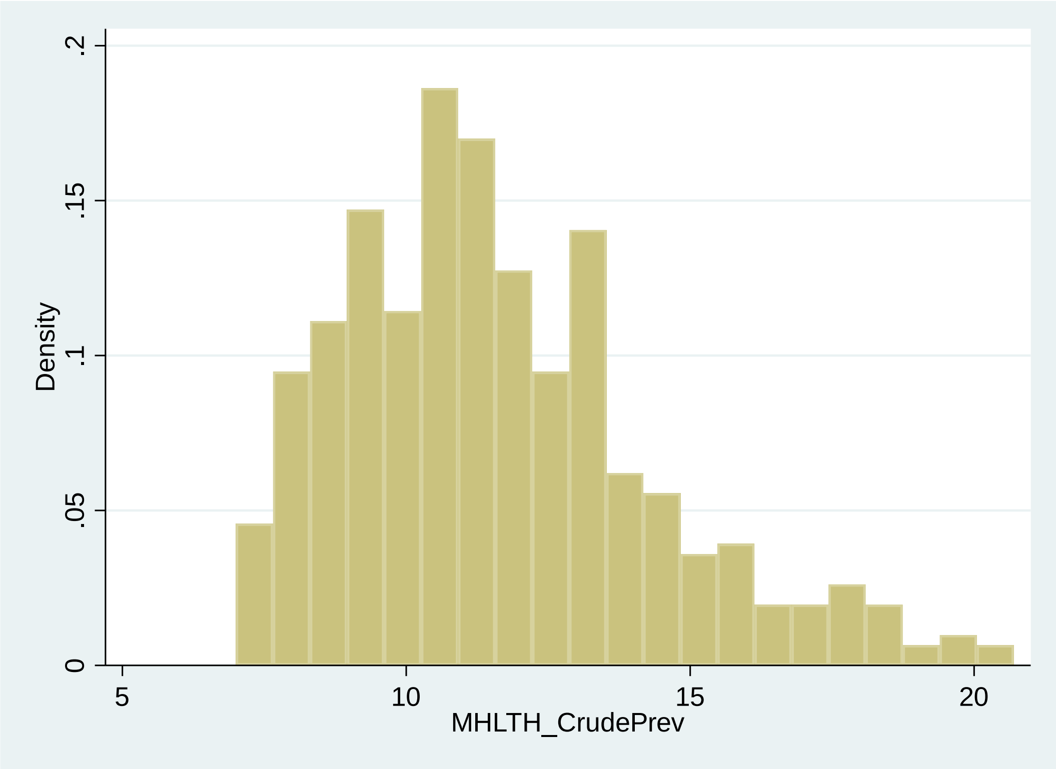

Figure 17. Histogram *percentage of respondents who report that 14 or more days during the past 30 days during which their mental health was not good.*

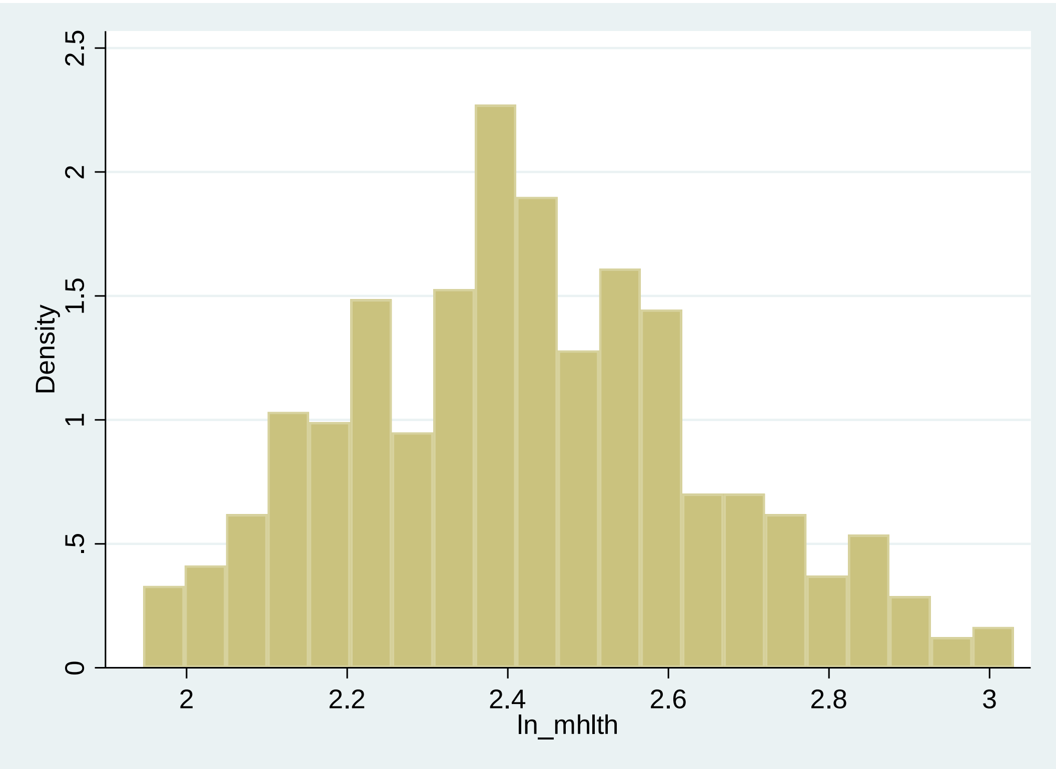

Figure 18. Histogram of natural log of *percentage of respondents who report that 14 or more days during the past 30 days during which their mental health was not good.*

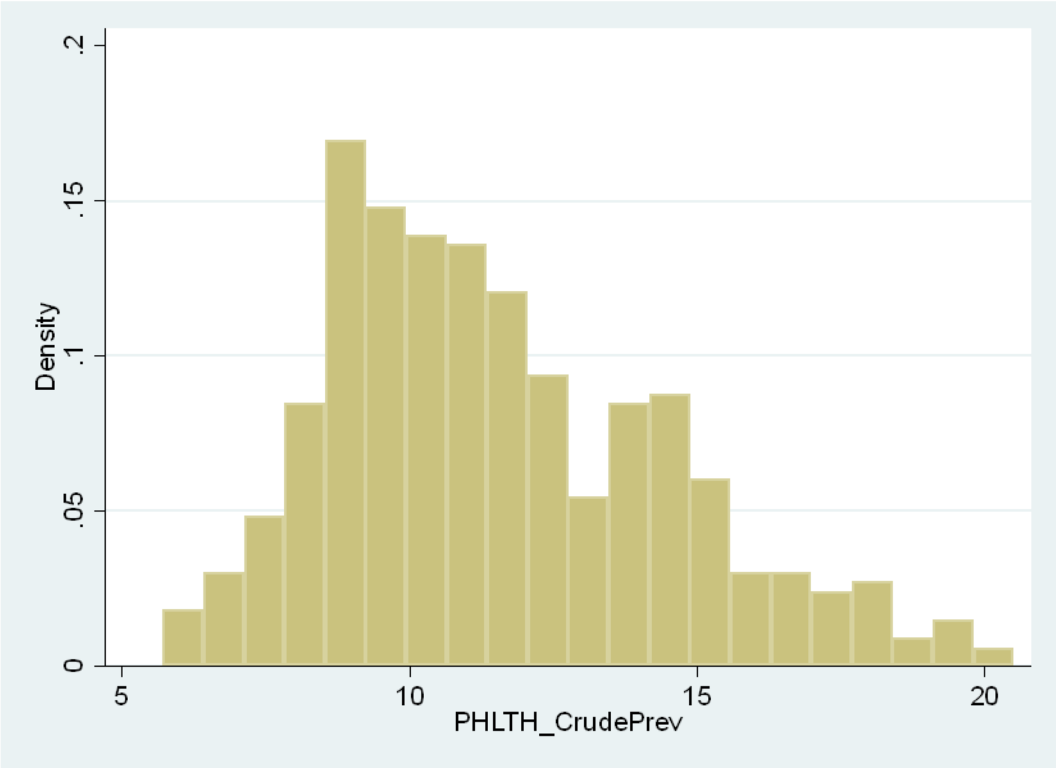

Figure 19. Histogram of *percentage of respondents who report that 14 or more days during the past 30 days during which their physical health was not good.*

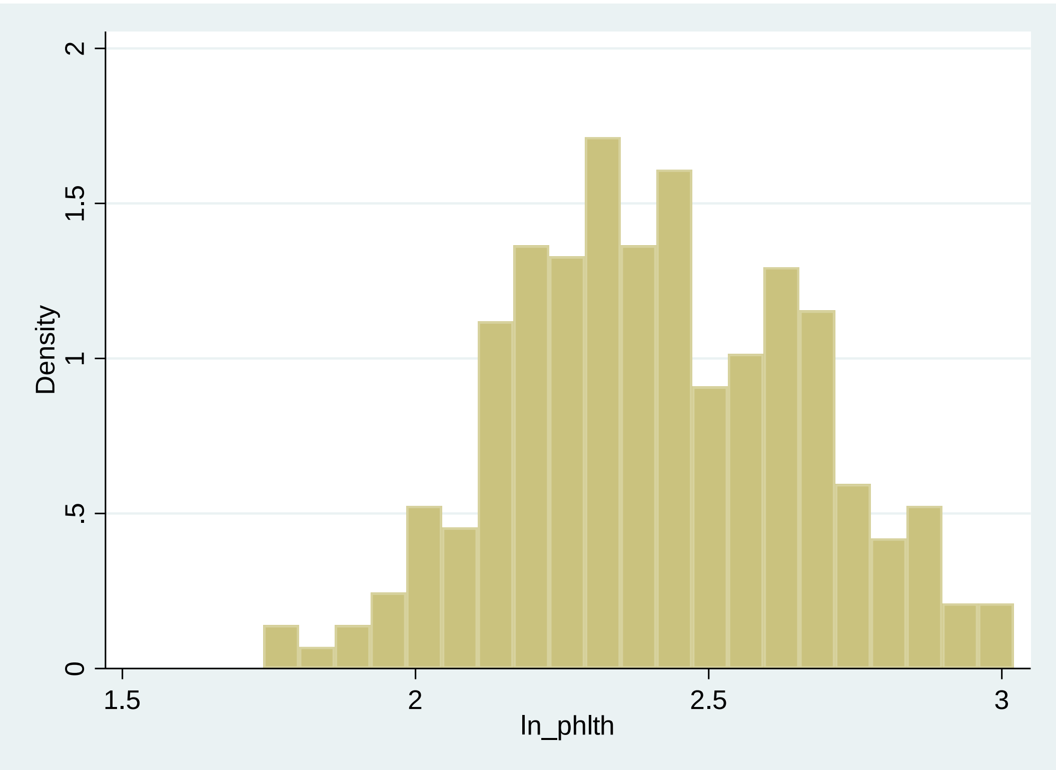

Figure 20. Histogram of natural log of *percentage of respondents who report that 14 or more days during the past 30 days during which their mental health was not good.*

Appendix 2. Regressions Physical Health Census Tract Averages

Natural Log *Physical Health* County level	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]	Number of obs	463
Gini Coefficient of City	-.669365	.1765491	-3.79	0.000	-101.632	-.3224102	F(8, 454)	247.44
Gini at Census Tract Level	.0796629	.1264896	0.63	0.529	-.1689148	.3282406	Prob > F	0.0000
Median income	.0000597	.0000354	1.69	0.092	-9.81e-06	.0001293	R-squared	0.8134
Gross Rent House	-.0000719	.0000169	-4.25	0.000	-.0001052	-.0000387	Adj R-squared	0.8102
Labor Force Participation Rate	-.0046489	.0008252	-5.63	0.000	-.0062706	-.0030272		
Unemployment Rate	.0049979	.0019942	2.51	0.013	.0010789	.0089169		
Percentage graduated high school	-.0110937	.0005595	-19.83	0.000	-.0121932	-.0099942		
Percentage below poverty level	.0016553	.0009244	1.79	0.074	-.0001613	.0034719		
Constant	3.934617	.1017238	38.68	0.000	3.734709	4.134525		

Table 17. Regression that shows the relationship between the natural log of *physical health* and a number of predictors at county level.

Natural Log *Physical Health* State level	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Gini Coefficient of County	-1.048194	.0779886	-13.44	0.000	-1.201.084	-.895303
Gini at Census Tract Level	-.1543194	.0330922	-4.66	0.000	-.2191941	-.0894447
Median income	-2.00e-06	1.06e-07	-18.89	0.000	-2.20e-06	-1.79e-06
Gross Rent House	-.0000873	5.99e-06	-14.59	0.000	-.0000991	-.0000756
Labor Force Participation Rate	-.0069746	.0002209	-31.57	0.000	-.0074077	-.0065414
Unemployment Rate	.0060989	.0004625	13.19	0.000	.0051922	.0070056
Percentage graduated high school	-.0098408	.0001637	-60.13	0.000	-.0101617	-.00952
Percentage below poverty level	.0011172	.0002536	4.41	0.000	.0006201	.0016143
Constant	4.462421	.0410134	108.80	0.000	4.382017	4.542824

Number of obs	5,185
F(8, 5176)	3631.08
Prob > F	0.0000
R-squared	0.8488
Adj R-squared	0.8485

Table 18. Regression that shows the relationship between the natural log of *physical health* and a number of predictors at state level.

Natural log *Physical Health* Country level	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]	Number of obs	26,394
Gini Coefficient of State	1.011514	.0588045	17.20	0.000	.8962537	1.126774	F(8, 26385)	13257.21
Gini at Census Tract Level	-.4220755	.0162729	-25.94	0.000	-.4539713	-.3901797	Prob > F	0.0000
Median income	-2.88e-06	6.52e-08	-44.15	0.000	-3.00e-06	-2.75e-06	R-squared	0.8008
Gross Rent House	-.0001097	3.46e-06	-31.69	0.000	-.0001165	-.0001029	Adj R-squared	0.8007
Labor Force Participation Rate	-.0077078	.0001118	-68.95	0.000	-.0079269	-.0074886		
Unemployment Rate	.0091251	.0001983	46.03	0.000	.0087365	.0095137		
Percentage graduated high school	-.0096096	.0000986	-97.51	0.000	-.0098028	-.0094165		
Percentage below poverty level	.0013962	.0001251	11.16	0.000	.0011509	.0016414		
Constant	3.686501	.031291	117.81	0.000	3.625169	3.747833		

Table 19. Regression that shows the relationship between the natural log of *physical health* and a number of predictors at country level.

Appendix 3. Null Models Multilevel Analysis Mental Health

Level	ICC	Std. Err.	[95% Conf.	Interval]
City	.3412268	.0910289	.1897681	.5339112

Table 20. The intraclass correlation of the null model with the natural log of mental health as dependent variable, with county as highest geographical level and city as contextual effect.

Level	ICC	Std. Err.	[95% Conf.	Interval]
County	.2213876	.0507874	.1376356	.3362327

Table 21. The intraclass correlation of the null model with the natural log of mental health as dependent variable with state as highest geographical level and county as contextual effect.

Level	ICC	Std. Err.	[95% Conf.	Interval]
State	.2057431	.0336496	.1474969	.2794507

Table 22. The intraclass correlation of the null model with the natural log of mental health as dependent variable with country as highest geographical level and state as contextual effect.

Appendix 4. Null Models Multilevel Analysis Physical Health

Level	ICC	Std. Err.	[95% Conf.	Interval]
City	.3808595	.0947019	.2187367	.5747456

Table 23. The intraclass correlation of the null model with the natural log of physical health as dependent variable, with county as highest geographical level and city as contextual effect.

Level	ICC	Std. Err.	[95% Conf.	Interval]
County	.2087124	.0489674	.1285509	.3204781

Table 24. The intraclass correlation of the null model with the natural log of physical health as dependent variable with state as highest geographical level and county as contextual effect.

Level	ICC	Std. Err.	[95% Conf.	Interval]
State	.1639581	.0291633	.1144515	.2293332

Table 25. The intraclass correlation of the null model with the natural log of physical health as dependent variable with country as highest geographical level and state as contextual effect.

Appendix 5. Multilevel Analysis Mental Health with Predictors

Natural Log *Mental Health* County level	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gini Coefficient of City	-.2657409	.2575366	-1.03	0.302	-.7705033	.2390215
Gini at Census Tract Level	-.3550456	.084024	-4.23	0.000	-.5197296	-.1903617
Median income	.0000804	.0000228	3.53	0.000	.0000357	.0001251
Gross Rent House	-.0000633	.0000116	-5.45	0.000	-.0000861	-.0000406
Labor Force Participation Rate	.0034558	.0005651	6.12	0.000	.0023482	.0045634
Unemployment Rate	.004046	.0012965	3.12	0.002	.0015049	.0065871
Percentage graduated high school	-.0077854	.0004284	-18.17	0.000	-.008625	-.0069458
Percentage below poverty level	.0086036	.000616	13.97	0.000	.0073963	.0098109
Constant	3.036689	.1239241	24.50	0.000	2.793803	3.279576

Level	ICC	Std. Err.	[95% Conf.	Interval]
City	.2095097	.0735879	.0998624	.3876949

Table 26. Regression coefficients and the intraclass correlation for the county-model with *mental health* as dependent variable.

Natural Log *Mental Health* State level	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gini Coefficient of County	-1.059428	.4694073	-2.26	0.024	-1.979449	-.1394064
Gini at Census Tract Level	-.3989309	.0263408	-15.14	0.000	-.450558	-.3473038
Median income	-2.06e-06	8.37e-08	-24.66	0.000	-2.23e-06	-1.90e-06
Gross Rent House	-.0000318	4.89e-06	-6.50	0.000	-.0000413	-.0000222
Labor Force Participation Rate	.0021005	.0001727	12.16	0.000	.0017619	.002439
Unemployment Rate	.0037376	.0003678	10.16	0.000	0030166	.0044586
Percentage graduated high school	-.0068059	.0001341	-50.77	0.000	-.0070686	-.0065431
Percentage below poverty level	.0061772	.0001968	31.38	0.000	.0057914	.006563
Constant	3.626722	.2186823	16.58	0.000	3.198113	4.055332

Level	ICC	Std. Err.	[95% Conf.	Interval]
County	.1803564	.0454164	.1075434	.2866347

Table 27. Regression coefficients and the intraclass correlation for the state-model with *mental health* as dependent variable.

Natural Log *Mental Health* Country level	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gini Coefficient of State	1.494941	.5998674	2.49	0.013	.319223	2.67066
Gini at Census Tract Level	-.5678493	.0101398	-56.00	0.000	-.587723	-.5479756
Median income	-2.77e-06	4.10e-08	-67.69	0.000	-2.86e-06	-2.69e-06
Gross Rent House	-.000028	2.41e-06	-11.60	0.000	-.0000327	-.0000232
Labor Force Participation Rate	.0011956	.0000698	17.12	0.000	.0010588	.0013324
Unemployment Rate	.0049981	.0001273	39.27	0.000	.0047487	.0052475
Percentage graduated high school	-.0062459	.0000649	-96.18	0.000	-.0063731	-.0061186
Percentage below poverty level	.0067644	.0000779	86.88	0.000	.0066118	.0069171
Constant	2.531498	.2791075	9.07	0.000	1.984457	3.078538

Level	ICC	Std. Err.	[95% Conf.	Interval]
State	.4368531	.0509888	.3407018	.5379968

Table 28. Regression coefficients and the intraclass correlation for the country-model with *mental health* as dependent variable.

Appendix 6. Multilevel Analysis Physical Health with Predictors

Natural Log *Physical Health* County level	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gini Coefficient of City	-.5363051	.3406901	-1.57	0.115	-1.204.045	.1314352
Gini at Census Tract Level	.008562	.1196904	0.07	0.943	-.2260268	.2431509
Median income	.0000796	.0000325	2.45	0.014	.0000159	.0001433
Gross Rent House	-.0000491	.0000165	-2.97	0.003	-.0000815	-.0000167
Labor Force Participation Rate	-.004876	.0008041	-6.06	0.000	-.006452	-.0033001
Unemployment Rate	.0046652	.0018482	2.52	0.012	.0010428	.0082875
Percentage graduated high school	-.011452	.0006083	-18.83	0.000	-.0126443	-.0102597
Percentage below poverty level	.0031955	.0008774	3.64	0.000	.0014757	.0049152
Constant	3.890499	.1657655	23.47	0.000	3.565605	4.215393

Level	ICC	Std. Err.	[95% Conf.	Interval]
City	.1795688	.0655412	.0838449	.3435923

Table 29. Regression coefficients and the intraclass correlation for the county-model with *physical health* as dependent variable.

Natural Log *Physical Health* State level	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gini Coefficient of County	-1.37513	.4507434	-3.05	0.002	-2.258.571	-.4916893
Gini at Census Tract Level	-.0578884	.0336076	-1.72	0.085	-.1237581	.0079812
Median income	-1.70e-06	1.07e-07	-15.95	0.000	-1.91e-06	-1.49e-06
Gross Rent House	-.0000833	6.23e-06	-13.37	0.000	-.0000955	-.0000711
Labor Force Participation Rate	-.0064734	.0002204	-29.37	0.000	-.0069054	-.0060414
Unemployment Rate	.0057585	.0004689	12.28	0.000	.0048394	.0066777
Percentage graduated high school	-.0101934	.0001706	-59.75	0.000	-.0105278	-.009859
Percentage below poverty level	.0012562	.0002513	5.00	0.000	.0007636	.0017488
Constant	4.559147	.2100363	21.71	0.000	4.147483	4.97081

Level	ICC	Std. Err.	[95% Conf.	Interval]
County	.1056627	.0311281	.0583348	.1838901

Table 30. Regression coefficients and the intraclass correlation for the county-model with *physical health* as dependent variable.

Natural Log *Physical Health* Country level	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gini Coefficient of State	1.199073	.5482393	2.19	0.029	.1245435	2.273602
Gini at Census Tract Level	-.401378	.0153869	-26.09	0.000	-.4315358	-.3712202
Median income	-2.56e-06	6.22e-08	-41.11	0.000	-2.68e-06	-2.44e-06
Gross Rent House	-.0000979	3.65e-06	-26.78	0.000	-.000105	-.0000907
Labor Force Participation Rate	-.0072359	.000106	-68.30	0.000	-.0074436	-.0070283
Unemployment Rate	.0092089	.0001931	47.69	0.000	.0088304	.0095874
Percentage graduated high school	-.0106955	.0000985	-108.55	0.000	-.0108887	-.0105024
Percentage below poverty level	.0012824	.0001182	10.85	0.000	.0010508	.001514
Constant	3.635037	.2554255	14.23	0.000	3.134412	4.135661

Level	ICC	Std. Err.	[95% Conf.	Interval]
State	.2153345	.0370295	.1515367	.2966021

Table 31. Regression coefficients and the intraclass correlation for the country-model with *physical health* as dependent variable.

Appendix 7. Regressions between Physical Health and State

Number of days physical health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
State (ref. cat. California)						
Alabama	1.365984	.1362811	10.02	0.000	1.098878	1.633091
Alaska	.4538909	.1871158	2.43	0.015	.0871498	.8206321
Arizona	1.003377	.119741	8.38	0.000	.768688	1.238065
Arkansas	2.03336	.1493703	13.61	0.000	1.740598	2.326121
Colorado	-.1242215	.1113339	-1.12	0.265	-.3424324	.0939894
Connecticut	-.1481557	.1195006	-1.24	0.215	-.3823731	.0860618
Delaware	-.0234749	.1643357	0.14	0.886	-.3455677	.298618
District of Columbia	-.5012464	.1677187	-2.99	0.003	-.8299699	-.1725229
Florida	1.093167	.0958678	11.40	0.000	.9052694	1.281.065
Georgia	.6602191	.1486246	4.44	0.000	.3689196	.9515186
Hawaii	-.0970745	.1298434	0.75	0.455	-.3515635	.1574145
Idaho	.5592031	.1498508	3.73	0.000	.2655001	.852906
Illinois	.4017717	.1542469	2.60	0.009	.0994525	.7040908
Indiana	.7851945	.1196501	6.56	0.000	.5506839	1.019.705
Iowa	-.4011032	.1344759	-2.98	0.003	-.6646718	-.1375347
Kansas	-.2594239	.1169026	-2.22	0.026	-.4885494	-.0302984
Kentucky	1.478653	.1219122	12.13	0.000	1.239709	1.717597
Louisiana	1.161235	.1498206	7.75	0.000	.8675918	1.454879
Maine	.4426183	.1226691	3.61	0.000	.2021906	.683046
Maryland	-.0861459	.1065176	0.81	0.419	-.2949171	.1226253
Massachusetts	.0139009	.129162	0.11	0.914	-.2392527	.2670544
Michigan	.6883877	.1169532	5.89	0.000	.4591629	.9176124
Minnesota	-.567742	.1084787	-5.23	0.000	-.7803568	-.3551272
Mississippi	.9229055	.1517532	6.08	0.000	.6254739	1.220337
Missouri	1.360965	.135365	10.05	0.000	1.095654	1.626276
Montana	.5167031	.1431169	3.61	0.000	.2361984	.7972078
Nebraska	-.322998	.1107756	-2.92	0.004	-.5401148	-.1058812
Nevada	.840382	.1601181	5.25	0.000	.5265554	1.154209
New Hampshire	.2673543	.1395966	1.92	0.055	-.0062507	.5409593
New Jersey	.3547358	.1326127	2.67	0.007	.0948191	.6146525
New Mexico	1.160022	.142544	8.14	0.000	.88064	1.439404

Number of obs	467,586
LR chi2(50)	2160.17
Prob > chi2	0.0000
Pseudo R2	0.0006

New York	.553504	.0967717	5.72	0.000	.3638344	.7431735
North Carolina	.2633214	.1390024	1.89	0.058	-.009119	.5357617
North Dakota	-.5206363	.1452095	-3.59	0.000	-.8052425	-.2360301
Ohio	.7373495	.1161362	6.35	0.000	.5097262	.9649727
Oklahoma	1.197145	.1369428	8.74	0.000	.9287411	1.465.548
Oregon	.2504296	.1482296	1.69	0.091	-.0400959	.5409551
Pennsylvania	.2670058	.1370067	1.95	0.051	-.0015232	.5355347
Rhode Island	.579548	.1475576	3.93	0.000	.2903396	.8687564
South Carolina	1.113661	.1193998	9.33	0.000	.8796413	1.347.681
South Dakota	-.0695552	.1446274	0.48	0.631	-.3530204	.21391
Tennessee	1.609952	.1422697	11.32	0.000	1.331108	1.888796
Texas	.5528325	.1181295	4.68	0.000	.3213023	.7843627
Utah	-.1260212	.119653	-1.05	0.292	-.3605373	.1084949
Vermont	.2471533	.1389264	1.78	0.075	-.0251382	.5194448
Virginia	.0707431	.1264053	0.56	0.576	-.1770074	.3184936
Washington	.3097682	.1124085	2.76	0.006	.0894511	.5300854
West Virginia	1.914373	.135156	14.16	0.000	1.649471	2.179274
Wisconsin	.2074843	.1486731	1.40	0.163	-.0839103	.4988789
Wyoming	.3274995	.1577942	2.08	0.038	.0182277	.6367713
Constant	3.907555	.0836333	46.72	0.000	3.743636	4.071474

Table 32. Tobit regression between number of days physical health was not good and the state where an individual is living.

Appendix 8. Regressions Mental and Physical Health without Gini-Coefficient

Number of obs	459,298
LR chi2(76)	51442.37
Prob > chi2	0.0000
Pseudo R2	0.0161

Number of days mental health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
State (ref. cat. California)						
Alabama	.1338985	.1137037	1.18	0.239	-.0889573	.3567542
Alaska	-.2283525	.1565056	-1.46	0.145	-.5350986	.0783936
Arizona	.1609665	.1003972	1.60	0.109	-.035809	.357742
Arkansas	.5095761	.1246706	4.09	0.000	.2652256	.7539265
Colorado	.0579213	.0931772	0.62	0.534	-.1247031	.2405458
Connecticut	.0673882	.100185	0.67	0.501	-.1289714	.2637478
Delaware	-.1474277	.1368797	-1.08	0.281	-.4157077	.1208523
District of Columbia	-.3982739	.1412082	-2.82	0.005	-.6750375	-.1215102
Florida	-.0011105	.0804622	0.01	0.989	-.1588139	.1565929
Georgia	-.3290988	.1240423	-2.65	0.008	-.5722178	-.0859798
Hawaii	-.1886276	.1083315	-1.74	0.082	-.400954	.0236988
Idaho	.2456935	.125081	1.96	0.049	.0005385	.4908485
Illinois	-.1320943	.1282475	-1.03	0.303	-.3834555	.1192669
Indiana	.1548028	.1001467	1.55	0.122	-.0414816	.3510873
Iowa	-.1844709	.1122621	-1.64	0.100	-.4045011	.0355593
Kansas	-.2334449	.0980019	-2.38	0.017	-.4255256	-.0413642
Kentucky	.2180723	.1018149	2.14	0.032	.0185183	.4176264
Louisiana	.1313848	.1249132	1.05	0.293	-.1134413	.3762109
Maine	.2218316	.1024676	2.16	0.030	.0209982	.422665
Maryland	.0002334	.0893424	0.00	0.998	-.1748749	.1753418
Massachusetts	.3215077	.1084143	2.97	0.003	.109019	.5339965
Michigan	.2821963	.0977926	2.89	0.004	.0905258	.4738668
Minnesota	-.3386551	.0907867	-3.73	0.000	-.5165942	-.1607159

Mississippi	-.3002526	.1262891	-2.38	0.017	-.5477754	-.0527299
Missouri	.3401589	.1131997	3.00	0.003	.118291	.5620268
Montana	-.1189349	.1195163	-1.00	0.320	-.3531833	.1153134
Nebraska	-.3175226	.0925678	-3.43	0.001	-.4989527	-.1360925
Nevada	.6136847	.13357	4.59	0.000	.3518917	.8754777
New Hampshire	.2205438	.116793	1.89	0.059	-.008367	.4494545
New Jersey	-.0312486	.1110009	0.28	0.778	-.248807	.1863098
New Mexico	.1446819	.1189321	1.22	0.224	-.0884214	.3777852
New York	.0400236	.0811033	0.49	0.622	-.1189363	.1989835
North Carolina	.0735942	.1158803	0.64	0.525	-.1535277	.300716
North Dakota	-.5490898	.121039	-4.54	0.000	-.7863225	-.3118571
Ohio	.1319707	.0972001	1.36	0.175	-.0585386	.3224799
Oklahoma	.3914911	.1143122	3.42	0.001	.1674427	.6155396
Oregon	.5612337	.1239436	4.53	0.000	.3183081	.8041593
Pennsylvania	.3780801	.1142857	3.31	0.001	.1540836	.6020766
Rhode Island	.301411	.1236753	2.44	0.015	.0590112	.5438107
South Carolina	.2957847	.0996099	2.97	0.003	.1005525	.491017
South Dakota	-.4862872	.1205742	-4.03	0.000	-.7226088	-.2499655
Tennessee	.5022783	.1186917	4.23	0.000	.2696462	.7349103
Texas	-.133638	.0987745	-1.35	0.176	-.3272329	.0599569
Utah	.3152241	.1002254	3.15	0.002	.1187854	.5116629
Vermont	.386784	.1159046	3.34	0.001	.1596146	.6139535
Virginia	-.138991	.1057253	-1.31	0.189	-.3462093	.0682273
Washington	.1537096	.0940594	1.63	0.102	-.0306439	.338063
West Virginia	.7228463	.1126941	6.41	0.000	.5019694	.9437232
Wisconsin	.0587811	.1247508	0.47	0.638	-.1857267	.3032888
Wyoming	-.0107477	.1314299	0.08	0.935	-.2683463	.2468508
Female (ref. cat. *Male*)	.9112179	.0226478	40.23	0.000	.8668289	.9556069
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.1979589	.0709319	2.79	0.005	.0589345	.3369832
Age 30 to 34	.0826089	.0707305	1.17	0.243	-.0560208	.2212385
Age 35 to 39	-.0309123	.0703231	0.44	0.660	-.1687434	.1069189
Age 40 to 44	-.1192547	.0707405	-1.69	0.092	-.257904	.0193946

Age 45 to 49	-.2162221	.0681926	-3.17	0.002	-.3498776	-.0825667
Age 50 to 54	-.5652212	.0656046	-8.62	0.000	-.6938042	-.4366381
Age 55 to 59	-.9923603	.0642251	-15.45	0.000	-1.11824	-.866481
Age 60 to 64	-1.614546	.0643222	-25.1	0.000	-1.740616	-1.488477
Age 65 to 69	-2.057862	.0669943	-30.72	0.000	-2.189169	-1.926556
Age 70 to 74	-2.500788	.0705462	-35.45	0.000	-2.639056	-2.362519
Age 75 to 79	-2.853039	.0745446	-38.27	0.000	-2.999144	-2.706934
Age 80 or older	-3.311842	.0723513	-45.77	0.000	-3.453648	-3.170035
Married (ref. cat. *Not Married*)	-1.141371	.0234718	-48.63	0.000	-1.187375	-1.095367
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-3.785945	.0798156	-47.43	0.000	-3.942381	-3.629509
Self-employed	-3.610631	.0863669	-41.81	0.000	-3.779908	-3.441355
Out of work for less than 1 year	-.8667949	.1094793	-7.92	0.000	-1.081371	-.6522188
A homemaker	-3.105318	.0918782	-33.8	0.000	-3.285396	-2.925239
A student	-3.144811	.1086596	-28.94	0.000	-3.35778	-2.931841
Retired	-2.738282	.0840053	-32.6	0.000	-2.90293	-2.573634
Unable to work	3.873981	.087339	44.36	0.000	3.7028	4.045163
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.7888327	.3017415	2.61	0.009	.1974287	1.380237
Grades 9 through 11 (Some high school)	1.247422	.2971854	4.20	0.000	.6649479	1.829896
Grade 12 or GED (High school graduate)	.5315771	.2939952	1.81	0.071	-.0446443	1.107799
College 1 year to 3 years (Some college	.7158453	.2940378	2.43	0.015	.1395403	1.29215

or technical school)						
College 4 years or more (College graduate)	-.0214835	.2939299	0.07	0.942	-.597577	.5546101
Constant	7.01339	.3141733	22.33	0.000	6.398569	7.630109

Table 33. Tobit regression between number of days mental health was not good and a number of predictors.

Number of days physical health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]	Number of obs	457,052
							LR chi2(76)	86836.72
State (ref. cat. California)							Prob > chi2	0.0000
Alabama	-.0912839	.1258609	0.73	0.468	-.3379674	.1553996	Pseudo R2	0.0263
Alaska	.3614194	.173373	2.08	0.037	.0216137	.7012251		
Arizona	.2499469	.1110562	2.25	0.024	.0322802	.4676137		
Arkansas	.4793466	.1380841	3.47	0.001	.2087059	.7499872		
Colorado	-.1213844	.1030888	-1.18	0.239	-.3234353	.0806664		
Connecticut	-.2860565	.1108075	-2.58	0.010	-.5032357	-.0688772		
Delaware	-.4819634	.1517056	-3.18	0.001	-.7793017	-.1846252		
District of Columbia	-.7127979	.156503	-4.55	0.000	-1.019.539	-.4060568		
Florida	.1045373	.0889766	1.17	0.240	-.0698541	.2789286		
Georgia	-.236258	.1374111	-1.72	0.086	-.5055795	.0330634		
Hawaii	-.0555693	.1198201	0.46	0.643	-.2904131	.1792744		
Idaho	.1840378	.1385526	1.33	0.184	-.087521	.4555967		
Illinois	.2407662	.1418206	1.70	0.090	-.0371978	.5187302		
Indiana	.0132523	.1108187	0.12	0.905	-.2039489	.2304536		
Iowa	-.5028431	.1241626	-4.05	0.000	-.746198	-.2594882		
Kansas	-.4177402	.1085313	-3.85	0.000	-.6304582	-.2050223		
Kentucky	.3384734	.1126944	3.00	0.003	.1175958	.559351		
Louisiana	-.0308008	.1384004	0.22	0.824	-.3020612	.2404596		
Maine	-.1316586	.1134135	-1.16	0.246	-.3539456	.0906285		
Maryland	-.358282	.0987975	-3.63	0.000	-.551922	-.1646421		
Massachusetts	-.1592496	.1199661	-1.33	0.184	-.3943794	.0758803		
Michigan	.1380334	.108154	1.28	0.202	-.0739451	.3500119		
Minnesota	-.3535526	.1003783	-3.52	0.000	-.5502909	-.1568142		
Mississippi	-.5423668	.1399691	-3.87	0.000	-.8167019	-.2680318		
Missouri	.4777093	.1252615	3.81	0.000	.2322006	.7232179		
Montana	.1316107	.1322121	1.00	0.320	-.1275209	.3907423		
Nebraska	-.3562665	.102386	-3.48	0.001	-.55694	-.155593		
Nevada	.4078372	.14803	2.76	0.006	.1177029	.6979715		
New Hampshire	-.1423017	.1291206	-1.1	0.270	-.395374	.1107707		
New Jersey	.0105749	.1228673	0.09	0.931	-.2302412	.251391		
New Mexico	.378866	.1315713	2.88	0.004	.1209903	.6367418		
New York	-.0398186	.089681	0.44	0.657	-.2155906	.1359533		
North Carolina	-.2950866	.1282825	-2.3	0.021	-.5465163	-.0436568		
North Dakota	-.4519038	.1340864	-3.37	0.001	-.714709	-.1890986		
Ohio	.0015399	.1074745	0.01	0.989	-.2091069	.2121866		
Oklahoma	.3246779	.1266743	2.56	0.010	.0764003	.5729556		
Oregon	.1665818	.137434	1.21	0.225	-.1027846	.4359482		

Pennsylvania	.0937267	.1263796	0.74	0.458	-.1539734	.3414268
Rhode Island	-.0407625	.1368502	0.3	0.766	-.3089847	.2274597
South Carolina	.0001812	.110491	0.00	0.999	-.2163778	.2167403
South Dakota	-.181503	.1332777	-1.36	0.173	-.4427231	.0797171
Tennessee	.5736959	.1316783	4.36	0.000	.3156105	.8317814
Texas	-.0075817	.1094122	0.07	0.945	-.2220263	.2068628
Utah	.2158667	.1108468	1.95	0.051	-.0013895	.433123
Vermont	-.0395011	.1282686	0.31	0.758	-.2909037	.2119014
Virginia	-.2011763	.1170448	-1.72	0.086	-.4305804	.0282278
Washington	.1012076	.104062	0.97	0.331	-.1027507	.3051658
West Virginia	.6285033	.12468	5.04	0.000	.3841343	.8728723
Wisconsin	.0807582	.1378525	0.59	0.558	-.1894284	.3509448
Wyoming	-.0071836	.1455135	0.05	0.961	-.2923856	.2780185
Female (ref. cat. *Male*)	.2001826	.0250754	7.98	0.000	.1510356	.2493297
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.6481484	.0784261	8.26	0.000	.4944357	.8018611
Age 30 to 34	.9218572	.0782194	11.79	0.000	.7685495	1.075165
Age 35 to 39	1.219131	.0777443	15.68	0.000	1.066755	1.371507
Age 40 to 44	1.47335	.0782138	18.84	0.000	1.320053	1.626646
Age 45 to 49	1.788847	.0754024	23.72	0.000	1.64106	1.936633
Age 50 to 54	1.989954	.0725514	27.43	0.000	1.847756	2.132153
Age 55 to 59	2.038892	.0710433	28.70	0.000	1.899649	2.178135
Age 60 to 64	1.779314	.071168	25.00	0.000	1.639827	1.918801
Age 65 to 69	1.750133	.074148	23.60	0.000	1.604806	1.895461
Age 70 to 74	1.835351	.0781089	23.50	0.000	1.68226	1.988442
Age 75 to 79	2.066931	.0826323	25.01	0.000	1.904974	2.228888
Age 80 or older	2.133401	.0802954	26.57	0.000	1.976024	2.290778
Married (ref. cat. *Not Married*)	-.7063265	.0259948	-27.17	0.000	-.7572755	-.6553774
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.356561	.0883662	-49.3	0.000	-4.529756	-4.183366
Self-employed	-4.24915	.0955999	-44.45	0.000	-4.436522	-4.061777
Out of work for less than 1 year	-1.945759	.1211079	-16.07	0.000	-2.183127	-1.708392
A homemaker	-3.045904	.1017537	-29.93	0.000	-3.245338	-2.84647
A student	-3.760577	.1202693	-31.27	0.000	-3.996301	-3.524853

Retired	-2.311119	.0930339	-24.84	0.000	-2.493462	-2.128775
Unable to work	8.617796	.0967662	89.06	0.000	8.428137	8.807454
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.6161222	.3366383	1.83	0.067	-.0436786	1.275923
Grades 9 through 11 (Some high school)	.5451637	.3315373	1.64	0.100	-.1046391	1.194967
Grade 12 or GED (High school graduate)	-.3261732	.3280003	0.99	0.320	-.9690437	.3166973
College 1 year to 3 years (Some college or technical school)	-.2779797	.3280422	0.85	0.397	-.9209323	.364973
College 4 years or more (College graduate)	-1.267155	.3279231	-3.86	0.000	-1.909874	-.6244362
Constant	6.164972	.3502354	17.60	0.000	5.478521	6.851422

Table 34. Tobit regression between number of days physical health was not good and a number of predictors.

Appendix 9. Regressions Mental and Physical Health with Gini-Coefficient

Number of days mental health was not good	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]	Number of obs	455,701
							LR chi2(27)	50687.71
Gini-Coefficient	1.128425	.5302294	2.13	0.033	.0891921	2.167659	Prob > chi2	0.0000
Female (ref. cat. *Male*)	.9142294	.0227398	40.20	0.000	.8696601	.9587987	Pseudo R2	0.0160
Age (ref. cat. *Age 18 to 24*)								
Age 25 to 29	.1980244	.0712968	2.78	0.005	.0582849	.337764		
Age 30 to 34	.0795832	.071076	1.12	0.263	-.0597237	.21889		
Age 35 to 39	-.0329837	.070672	0.47	0.641	-.1714986	.1055313		
Age 40 to 44	-.1117122	.0710559	-1.57	0.116	-.2509795	.0275552		
Age 45 to 49	-.2132435	.0684689	-3.11	0.002	-.3474404	-.0790466		
Age 50 to 54	-.5651671	.0658477	-8.58	0.000	-.6942265	-.4361077		
Age 55 to 59	-.9976323	.0644378	-15.48	0.000	-1.123928	-.8713363		
Age 60 to 64	-1.613443	.0645176	-25.01	0.000	-1.739895	-1.48699		
Age 65 to 69	-2.056311	.0671905	-30.6	0.000	-2.188002	-1.924619		
Age 70 to 74	-2.50402	.0707378	-35.4	0.000	-2.642663	-2.365376		
Age 75 to 79	-2.857577	.0747304	-38.24	0.000	-3.004047	-2.711108		
Age 80 or older	-3.326874	.0724966	-45.89	0.000	-3.468965	-3.184783		
Married (ref. cat. *Not Married*)	-1.144003	.0235347	-48.61	0.000	-1.19013	-1.097876		
Employment (ref. cat. *Out of work for 1 year or more*)								
Employed for wages	-3.7996	.0805287	-47.18	0.000	-3.957434	-3.641767		
Self-employed	-3.639024	.0870644	-41.8	0.000	-3.809668	-3.468381		
Out of work for less than 1 year	-.8704576	.1103375	-7.89	0.000	-1.086716	-.6541995		
A homemaker	-3.097417	.0925044	-33.48	0.000	-3.278723	-2.916112		
A student	-3.159184	.1094245	-28.87	0.000	-3.373653	-2.944715		

Retired	-2.739279	.0847163	-32.33	0.000	-2.90532	-2.573237
Unable to work	3.910259	.0880145	44.43	0.000	3.737753	4.082764
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.7976628	.3022918	2.64	0.008	.2051801	1.390146
Grades 9 through 11 (Some high school)	1.283572	.2977022	4.31	0.000	.7000846	1.867059
Grade 12 or GED (High school graduate)	.5639393	.2944785	1.92	0.055	-.0132295	1.141108
College 1 year to 3 years (Some college or technical school)	.7389539	.2945388	2.51	0.012	.161667	1.316241
College 4 years or more (College graduate)	.0031648	.294423	0.01	0.991	-.5738953	.5802248
Constant	6.531193	.3988474	16.38	0.000	5.749464	7.312921

Table 35. Tobit regression between number of days mental health was not good and a number of predictors with Gini-Coefficient added as predictor.

Number of days physical health was not good	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Gini-Coefficient	1.894995	.587426	3.23	0.001	.7436586	3.046332
Female (ref. cat. *Male*)	.1967801	.0251903	7.81	0.000	.1474079	.2461522
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.6362065	.0788735	8.07	0.000	.4816169	.7907962
Age 30 to 34	.9109128	.0786465	11.58	0.000	.7567682	1.065058
Age 35 to 39	1.216787	.0781727	15.57	0.000	1.063.571	1.370004
Age 40 to 44	1.473276	.0786063	18.74	0.000	1.31921	1.627342
Age 45 to 49	1.789395	.07575	23.62	0.000	1.640927	1.937863
Age 50 to 54	1.979765	.0728588	27.17	0.000	1.836964	2.122566
Age 55 to 59	2.022865	.0713164	28.36	0.000	1.883087	2.162643
Age 60 to 64	1.765279	.0714227	24.72	0.000	1.625292	1.905265
Age 65 to 69	1.735424	.0744052	23.32	0.000	1.589593	1.881256
Age 70 to 74	1.819589	.0783637	23.22	0.000	1.665998	1.973179
Age 75 to 79	2.056324	.0828819	24.81	0.000	1.893878	2.21877
Age 80 or older	2.106307	.0804991	26.17	0.000	1.948531	2.264083
Married (ref. cat. *Not Married*)	-.7015135	.0260772	-26.9	0.000	-.7526241	-.650403
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.410388	.0891866	-49.45	0.000	-4.585191	-4.235585
Self-employed	-4.300719	.0964066	-44.61	0.000	-4.489673	-4.111765
Out of work for less than 1 year	-1.965049	.1221083	-16.09	0.000	-2.204377	-1.72572
A homemaker	-3.055182	.1024881	-29.81	0.000	-3.256055	-2.854308
A student	-3.810421	.1211684	-31.45	0.000	-4.047907	-3.572935
Retired	-2.336236	.0938531	-24.89	0.000	-2.520186	-2.152287
Unable to work	8.630217	.0975478	88.47	0.000	8.439027	8.821408
Education (Ref. Cat. *Never*						

Number of obs	453,483
LR chi2(27)	85908.39
Prob > chi2	0.0000
Pseudo R2	0.0262

attended school or only kindergarten)						
Grades 1 through 8 (Elementary)	.6399563	.3374397	1.90	0.058	-.0214152	1.301328
Grades 9 through 11 (Some high school)	.5700983	.3322987	1.72	0.086	-.0811969	1.221394
Grade 12 or GED (High school graduate)	-.302982	.3287237	0.92	0.357	-.9472704	.3413065
College 1 year to 3 years (Some college or technical school)	-.2556476	.328784	0.78	0.437	-.9000541	.3887588
College 4 years or more (College graduate)	-1.263791	.3286548	-3.85	0.000	-1.907944	-.6196373
Constant	5.286795	.443747	11.91	0.000	4.417064	6.156525

Table 36. Tobit regression between number of days physical health was not good and a number of predictors with Gini-Coefficient added as predictor.

Appendix 10. Regressions with Change in Gini-Coefficient

Number of days mental health was not good	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Gini-Coefficient	1.14361	.5341772	2,14	0.032	.0966393	2.190581
Female (ref. cat. *Male*)	.9145529	.0227389	40,22	0.000	.8699854	.9591204
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.1972117	.0712938	2,77	0.006	.0574781	.3369454
Age 30 to 34	.0794244	.071073	1,12	0.264	-.0598766	.2187254
Age 35 to 39	-.0328825	.0706689	0,47	0.642	-.1713914	.1056264
Age 40 to 44	-.1130773	.0710532	-1,59	0.112	-.2523394	.0261848
Age 45 to 49	-.2150652	.0684665	-3,14	0.002	-.3492575	-.080873
Age 50 to 54	-.565235	.0658448	-8,58	0.000	-.6942888	-.4361812
Age 55 to 59	-.9972705	.0644356	-15,48	0.000	-1.123562	-.8709787
Age 60 to 64	-1.611491	.0645162	-24,98	0.000	-1.737941	-1.485041
Age 65 to 69	-2.053949	.0671889	-30,57	0.000	-2.185637	-1.922261
Age 70 to 74	-2.501472	.0707359	-35,36	0.000	-2.640112	-2.362832
Age 75 to 79	-2.854781	.0747284	-38,2	0.000	-3.001247	-2.708316
Age 80 or older	-3.323082	.0724963	-45,84	0.000	-3.465172	-3.180991
Married (ref. cat. *Not Married*)	-1.143883	.0235337	-48,61	0.000	-1.190008	-1.097758
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-3.798815	.0805261	-47,17	0.000	-3.956644	-3.640986
Self-employed	-3.637737	.0870628	-41,78	0.000	-3.808378	-3.467097
Out of work for less than 1 year	-.8692666	.1103334	-7,88	0.000	-1.085517	-.6530164
A homemaker	-3.097861	.0925007	-33,49	0.000	-3.279159	-2.916562
A student	-3.160761	.1094201	-28,89	0.000	-3.375221	-2.946301
Retired	-2.740058	.0847128	-32,35	0.000	-2.906092	-2.574023
Unable to work	3.909863	.0880107	44,42	0.000	3.737365	4.082362

Number of obs	455,701
LR chi2(29)	50727.59
Prob > chi2	0.0000
Pseudo R2	0.0160

Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.8033823	.3022808	2,66	0.008	.2109213	1.395843
Grades 9 through 11 (Some high school)	1.293154	.297694	4,34	0.000	.7096828	1.876625
Grade 12 or GED (High school graduate)	.5741891	.2944733	1,95	0.051	-.0029695	1.151348
College 1 year to 3 years (Some college or technical school)	.7511434	.294535	2,55	0.011	.1738639	1.328423
College 4 years or more (College graduate)	.0151917	.2944184	0,05	0.959	-.5618593	.5922427
Change Gini since 2011	-1.111185	1.99299	-5,58	0.000	-1.501805	-7.205652
Change Gini 2006	9.406541	1.838863	5,12	0.000	5.802426	1.301066
Constant	6.426248	.3992207	16,1	0.000	5.643788	7.208708

Table 37. Tobit regression between number of days mental health was not good and a number of predictors with Gini-Coefficient and changes in Gini added as predictors.

Number of days physical health was not good	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Gini-Coefficient	1.943321	.5918389	3.28	0.001	.7833354	3.103308
Female (ref. cat. *Male*)	.19689	.0251902	7.82	0.000	.147518	.246262
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.6358852	.0788732	8.06	0.000	.4812962	.7904742
Age 30 to 34	.9108082	.0786461	11.58	0.000	.7566642	1.064952
Age 35 to 39	1.216.837	.0781723	15.57	0.000	1.063622	1.370052
Age 40 to 44	1.472838	.0786063	18.74	0.000	1.318772	1.626.904
Age 45 to 49	1.788656	.0757502	23.61	0.000	1.640188	1.937125
Age 50 to 54	1.97978	.0728584	27.17	0.000	1.83698	2.122581
Age 55 to 59	2.023227	.0713169	28.37	0.000	1.883448	2.163006
Age 60 to 64	1.766269	.071424	24.73	0.000	1.62628	1.906258
Age 65 to 69	1.736501	.0744063	23.34	0.000	1.590667	1.882335
Age 70 to 74	1.820704	.0783647	23.23	0.000	1.667111	1.974296
Age 75 to 79	2.057485	.0828829	24.82	0.000	1.895037	2.219933
Age 80 or older	2.10795	.0805017	26.19	0.000	1.95017	2.265731
Married (ref. cat. *Not Married*)	-.7014917	.0260771	-26.9	0.000	-.7526019	-.6503814
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.409747	.0891871	-49.44	0.000	-4.584551	-4.234943
Self-employed	-4.299716	.0964085	-44.6	0.000	-4.488674	-4.110759
Out of work for less than 1 year	-1.964327	.1221083	-16.09	0.000	-2.203655	-1.724998
A homemaker	-3.05541	.1024878	-29.81	0.000	-3.256283	-2.854537
A student	-3.810788	.1211681	-31.45	0.000	-4.048274	-3.573302
Retired	-2.336358	.0938527	-24.89	0.000	-2.520306	-2.15241
Unable to work	8.630128	.0975472	88.47	0.000	8.438939	8.821318
Education (Ref. Cat. *Never attended school or only kindergarten*)						

Number of obs	453,483
LR chi2(29)	85913.85
Prob > chi2	0.0000
Pseudo R2	0.0263

Grades 1 through 8 (Elementary)	.6426182	.3374397	1.9	0.057	-.0187532	1.30399
Grades 9 through 11 (Some high school)	.5743319	.3323017	1.73	0.084	-.0769692	1.225633
Grade 12 or GED (High school graduate)	-.2980417	.3287296	0.91	0.365	-.9423417	.3462582
College 1 year to 3 years (Some college or technical school)	-.2499676	.3287916	0.76	0.447	-.894389	.3944539
College 4 years or more (College graduate)	-1.2583	.3286616	-3.83	0.000	-1.902467	-.6141333
Change Gini since 2011	-5.017003	2.208183	-2.27	0.023	-9.344973	-.6890315
Change Gini 2006	3.029774	2.038351	1.49	0.137	-.9653317	7.024879
Constant	5.24117	.4441769	11.80	0.000	4.370597	6.111743

Table 38. Tobit regression between number of days physical health was not good and a number of predictors with Gini-Coefficient and changes in Gini added as predictors.

Appendix 11. Spillover Effect Mental Health

Number of obs	384,953
LR chi2(29)	44584.56
Prob > chi2	0.0000
Pseudo R2	0.0167

Number of days mental health was not good.	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Female (ref. cat. *Male*)	.9311086	.0245276	37.96	0.000	.8830353	.979182
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.1031783	.0789174	1.31	0.191	-.0514974	.257854
Age 30 to 34	-.0488756	.0781751	0.63	0.532	-.2020964	.1043452
Age 35 to 39	-.1392695	.0776395	-1.79	0.073	-.2914405	.0129016
Age 40 to 44	-.2299793	.0781311	-2.94	0.003	-.3831139	-.0768447
Age 45 to 49	-.3725869	.075595	-4.93	0.000	-.5207509	-.2244229
Age 50 to 54	-.6899298	.0731199	-9.44	0.000	-.8332426	-.5466169
Age 55 to 59	-1.144975	.0717979	-15.95	0.000	-1.285696	-1.004253
Age 60 to 64	-1.688075	.07198	-23.45	0.000	-1.829154	-1.546996
Age 65 to 69	-2.138388	.0750092	-28.51	0.000	-2.285404	-1.991373
Age 70 to 74	-2.536347	.0792041	-32.02	0.000	-2.691585	-2.381109
Age 75 to 79	-2.943357	.0841085	-34.99	0.000	-3.108208	-2.778507
Age 80 or older	-3.368265	.0823994	-40.88	0.000	-3.529765	-3.206764
Married (ref. cat. *Not Married*)	-.9984845	.0258582	-38.61	0.000	-1.049166	-.9478031
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-3.625818	.0898728	-40.34	0.000	-3.801966	-3.44967
Self-employed	-3.494046	.0964025	-36.24	0.000	-3.682992	-3.3051
Out of work for less than 1 year	-.9678713	.1218736	-7.94	0.000	-1.20674	-.7290027
A homemaker	-2.974134	.1032545	-28.8	0.000	-3.17651	-2.771758
A student	-3.096555	.1230346	-25.17	0.000	-3.337699	-2.85541
Retired	-2.642799	.0941568	-28.07	0.000	-2.827343	-2.458254
Unable to work	3.792689	.0972293	39.01	0.000	3.602123	3.983256
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.7229329	.3599179	2.01	0.045	.0175046	1.428361
Grades 9 through 11 (Some high school)	1.220371	.3546326	3.44	0.001	.5253018	1.915441

Grade 12 or GED (High school graduate)	.6367892	.3512544	1.81	0.070	-.0516589	1.325237
College 1 year to 3 years (Some college or technical school)	.8559299	.3513152	2.44	0.015	.1673627	1.544497
College 4 years or more (College graduate)	.1595261	.3511959	0.45	0.650	-.5288075	.8478597
Gini-Coefficient	-7.255359	1.885155	-3.85	0.000	-1.095021	-3.560512
Income higher than 15,000 (ref. cat. lower than 15,000)	-5.661269	.9324561	-6.07	0.000	-7.488856	-3.833683
Interaction variable						
Higher than 15,000xGini	9.071917	1.976602	4.59	0.000	5.197.837	12.946
Constant	1.156794	.9639579	12.00	0.000	9.678613	13.45727

Table 39. Tobit regression between number of days mental health was not good and a number of predictors with interaction variable (Higher than 15,000xGini).

Number of days mental health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]	Number of obs	384,953
							LR chi2(29)	44879.16
Female (ref. cat. *Male*)	.9141302	.0245342	37.26	0.000	.866044	.9622164	Prob > chi2	0.0000
							Pseudo R2	0.0168
Age (ref. cat. *Age 18 to 24*)								
Age 25 to 29	.0970711	.0788885	1.23	0.219	-.0575481	.2516903		
Age 30 to 34	-.0567526	.0781475	0,73	0.468	-.2099194	.0964141		
Age 35 to 39	-.1409893	.0776105	-1,82	0.069	-.2931036	.011125		
Age 40 to 44	-.2304179	.0781014	-2,95	0.003	-.3834943	-.0773415		
Age 45 to 49	-.3625563	.0755626	-4,8	0.000	-.5106569	-.2144558		
Age 50 to 54	-.6739999	.0730877	-9,22	0.000	-.8172497	-.5307501		
Age 55 to 59	-1.128545	.0717667	-15,73	0.000	-1.269205	-.9878839		
Age 60 to 64	-1.678746	.0719517	-23,33	0.000	-1.819769	-1.537722		
Age 65 to 69	-2.132865	.0749803	-28,45	0.000	-2.279824	-1.985906		
Age 70 to 74	-2.531249	.0791739	-31,97	0.000	-2.686427	-2.37607		
Age 75 to 79	-2.949475	.0840757	-35,08	0.000	-3.114261	-2.784689		
Age 80 or older	-3.399714	.0823685	-41,27	0.000	-3.561154	-3.238274		
Married (ref. cat. *Not Married*)	-.9240643	.0261749	-35,3	0.000	-.9753664	-.8727623		
Employment (ref. cat. *Out of work for 1 year or more*)								
Employed for wages	-3.560795	.0899051	-39,61	0.000	-3.737006	-3.384584		
Self-employed	-3.448457	.0963759	-35,78	0.000	-3.637351	-3.259563		
Out of work for less than 1 year	-.9722931	.1217967	-7,98	0.000	-1.211011	-.7335752		
A homemaker	-2.944541	.1031973	-28,53	0.000	-3.146804	-2.742277		
A student	-3.058494	.1230136	-24,86	0.000	-3.299597	-2.817391		
Retired	-2.610199	.0941094	-27,74	0.000	-2.794651	-2.425748		
Unable to work	3.775224	.0971969	38.84	0.000	3.584721	3.965727		
Education (Ref. Cat. *Never attended*								

school or only kindergarten)						
Grades 1 through 8 (Elementary)	.7170063	.3597798	1.99	0.046	.0118485	1.422164
Grades 9 through 11 (Some high school)	1.234759	.3545007	3.48	0.000	.5399486	1.92957
Grade 12 or GED (High school graduate)	.7075372	.3511575	2.01	0.044	.0192789	1.395795
College 1 year to 3 years (Some college or technical school)	.9666306	.3512535	2.75	0.006	.2781842	1.655077
College 4 years or more (College graduate)	.3104265	.3511786	0.88	0.377	-.3778731	.9987261
Gini-Coefficient	-7.120645	1.412397	-5,04	0.000	-9.888901	-4.352388
Income higher than 20,000 (ref. cat. lower than 20,000)	-5.742681	.7267601	-7,9	0.000	-7.16711	-4.318253
Interaction variable						
Higher than 20,000xGini	9.463496	1.542516	6.14	0.000	6.440211	12.48678
Constant	11.1329	.7629624	14.59	0.000	9.63752	12.62829

Table 40. Tobit regression between number of days mental health was not good and a number of predictors with interaction variable (Higher than 20,000xGini).

Number of days mental health was not good.	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Female (ref. cat. *Male*)	.8958182	.0245451	36.50	0.000	.8477105	.9439259
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.0904799	.0788614	1.15	0.251	-.0640861	.2450459
Age 30 to 34	-.0516036	.078118	0.66	0.509	-.2047125	.1015052
Age 35 to 39	-.1289495	.0775806	-1.66	0.096	-.2810051	.0231061
Age 40 to 44	-.2102077	.0780688	-2.69	0.007	-.3632203	-.0571951
Age 45 to 49	-.3332102	.075533	-4.41	0.000	-.4812527	-.1851677
Age 50 to 54	-.6404654	.073062	-8.77	0.000	-.7836648	-.4972659
Age 55 to 59	-1.09246	.0717436	-15.23	0.000	-1.233075	-.9518448
Age 60 to 64	-1.650282	.0719289	-22.94	0.000	-1.791261	-1.509304
Age 65 to 69	-2.118186	.074954	-28.26	0.000	-2.265094	-1.971279
Age 70 to 74	-2.533173	.0791446	-32.01	0.000	-2.688294	-2.378052
Age 75 to 79	-2.957884	.0840447	-35.19	0.000	-3.122609	-2.793159
Age 80 or older	-3.425534	.0823441	-41.6	0.000	-3.586926	-3.264142
Married (ref. cat. *Not Married*)	-.8619142	.0264205	-32.62	0.000	-.9136975	-.8101309
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-3.532858	.0898034	-39.34	0.000	-3.70887	-3.356846
Self-employed	-3.437302	.0962551	-35.71	0.000	-3.625959	-3.248645
Out of work for less than 1 year	-.9950119	.1217158	-8.17	0.000	-1.233571	-.7564526
A homemaker	-2.943781	.1030869	-28.56	0.000	-3.145828	-2.741734
A student	-3.032641	.1229674	-24.66	0.000	-3.273654	-2.791629
Retired	-2.616746	.0939713	-27.85	0.000	-2.800927	-2.432565
Unable to work	3.778826	.0971568	38.89	0.000	3.588401	3.96925
Education (Ref. Cat. *Never attended*						

Number of obs	384,953
LR chi2(29)	45162.40
Prob > chi2	0.0000
Pseudo R2	0.0169

school or only kindergarten)						
Grades 1 through 8 (Elementary)	.7462283	.3596468	2.07	0.038	.0413313	1.451125
Grades 9 through 11 (Some high school)	1.266035	.354378	3.57	0.000	.5714647	1.960605
Grade 12 or GED (High school graduate)	.7494098	.3510449	2.13	0.033	.0613723	1.437447
College 1 year to 3 years (Some college or technical school)	1.046623	.3511685	2.98	0.003	.3583428	1.734902
College 4 years or more (College graduate)	.4523803	.3511618	1.29	0.198	-.2358863	1.140647
Gini-Coefficient	-5.501993	1.134271	-4.85	0.000	-7.725131	-3.278856
Income higher than 25,000 (ref. cat. lower than 25,000)	-5.165073	.6164688	-8.38	0.000	-6.373333	-3.956812
Interaction variable						
Higher than 25,000xGini	8.321966	1.31072	6.35	0.000	5.752995	10.89094
Constant	10.08397	.6510538	15.49	0.000	8.807928	11.36002

Table 41. Tobit regression between number of days mental health was not good and a number of predictors with interaction variable (Higher than 25,000xGini).

Number of days mental health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Female (ref. cat. *Male*)	.892632	.0245593	36.35	0.000	.8444965	.9407675
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.0645942	.0788853	0.82	0.413	-.0900187	.2192071
Age 30 to 34	-.0471525	.0781309	0.6	0.546	-.2002867	.1059817
Age 35 to 39	-.112125	.077593	-1.45	0.148	-.264205	.039955
Age 40 to 44	-.1846375	.0780826	-2.36	0.018	-.337677	-.031598
Age 45 to 49	-.3013977	.0755529	-3.99	0.000	-.4494792	-.1533162
Age 50 to 54	-.6140839	.0730833	-8.4	0.000	-.7573251	-.4708428
Age 55 to 59	-1.069269	.0717646	-14.9	0.000	-1.209926	-.9286128
Age 60 to 64	-1.638883	.0719454	-22.78	0.000	-1.779894	-1.497872
Age 65 to 69	-2.124299	.074966	-28.34	0.000	-2.27123	-1.977368
Age 70 to 74	-2.549196	.0791581	-32.2	0.000	-2.704344	-2.394049
Age 75 to 79	-2.989598	.0840641	-35.56	0.000	-3.154361	-2.824835
Age 80 or older	-3.460534	.0823769	-42.01	0.000	-3.62199	-3.299077
Married (ref. cat. *Not Married*)	-.8460592	.0266407	-31.76	0.000	-.8982743	-.7938442
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-3.599268	.0896524	-40.15	0.000	-3.774984	-3.423552
Self-employed	-3.495121	.0961576	-36.35	0.000	-3.683587	-3.306655
Out of work for less than 1 year	-1.0259	.121716	-8.43	0.000	-1.26446	-.7873399
A homemaker	-3.002461	.1030124	-29.15	0.000	-3.204362	-2.80056
A student	-3.043212	.1229799	-24.75	0.000	-3.284249	-2.802175
Retired	-2.687995	.0938574	-28.64	0.000	-2.871953	-2.504037

Number of obs	384,953
LR chi2(29)	45033.93
Prob > chi2	0.0000
Pseudo R2	0.0169

Unable to work	3.803982	.0971653	39.15	0.000	3.613541	3.994423
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.7781232	.359709	2.16	0.031	.0731042	1.483142
Grades 9 through 11 (Some high school)	1.280856	.3544444	3.61	0.000	.5861559	1.975557
Grade 12 or GED (High school graduate)	.7216223	.3510958	2.06	0.040	.0334851	1.40976
College 1 year to 3 years (Some college or technical school)	1.026366	.3512284	2.92	0.003	.3379688	1.714763
College 4 years or more (College graduate)	.4818431	.3512912	1.37	0.170	-.2066773	1.170363
Gini-Coefficient	-3.414092	.9518756	-3.59	0.000	-5.27974	-1.548445
Income higher than 35,000 (ref. cat. lower than 35,000)	-4.176794	.5575261	-7.49	0.000	-5.269529	-3.08406
Interaction variable						
Higher than 35,000xGini	6.516355	1.18725	5.49	0.000	418.938	8.843331
Constant	8.924898	.5820521	15.33	0.000	7.784093	10.0657

Table 42. Tobit regression between number of days mental health was not good and a number of predictors with interaction variable (Higher than 35,000xGini).

Number of days mental health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]	Number of obs	384,953
							LR chi2(29)	44873.15
Female (ref. cat. *Male*)	.9019044	.0245536	36.73	0.000	.85378	.9500288	Prob > chi2	0.0000
							Pseudo R2	0.0168
Age (ref. cat. *Age 18 to 24*)								
Age 25 to 29	.0390269	.0789209	0.49	0.621	-.1156558	.1937096		
Age 30 to 34	-.0442161	.0781469	0.57	0.572	-.1973816	.1089495		
Age 35 to 39	-.0935159	.0776095	-1.2	0.228	-.2456282	.0585963		
Age 40 to 44	-.1594531	.0781045	-2.04	0.041	-.3125357	-.0063706		
Age 45 to 49	-.2801336	.0755808	-3.71	0.000	-.4282696	-.1319976		
Age 50 to 54	-.5915751	.0731135	-8.09	0.000	-.7348754	-.4482748		
Age 55 to 59	-1.056548	.0717888	-14.72	0.000	-1.197252	-.9158439		
Age 60 to 64	-1.641012	.0719605	-22.8	0.000	-1.782053	-1.499972		
Age 65 to 69	-2.136699	.0749808	-28.5	0.000	-2.283659	-1.989739		
Age 70 to 74	-2.563923	.0791762	-32.38	0.000	-2.719106	-2.408741		
Age 75 to 79	-3.000033	.0840858	-35.68	0.000	-3.164839	-2.835228		
Age 80 or older	-3.452937	.0823919	-41.91	0.000	-3.614423	-3.291452		
Married (ref. cat. *Not Married*)	-.8622208	.0266583	-32.34	0.000	-.9144703	-.8099714		
Employment (ref. cat. *Out of work for 1 year or more*)								
Employed for wages	-3.699252	.0894284	-41.37	0.000	-3.874529	-3.523975		
Self-employed	-3.585271	.0960084	-37.34	0.000	-3.773445	-3.397097		
Out of work for less than 1 year	-1.068302	.1217206	-8.78	0.000	-1.306871	-.8297334		
A homemaker	-3.080455	.1029266	-29.93	0.000	-3.282188	-2.878722		
A student	-3.078248	.1229729	-25.03	0.000	-3.319272	-2.837225		
Retired	-2.792019	.0937221	-29.79	0.000	-2.975711	-2.608326		

Unable to work	3.818398	.0971824	39.29	0.000	3.627923	4.008872
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.7757322	.3597825	2.16	0.031	.0705693	1.480895
Grades 9 through 11 (Some high school)	1.243978	.3545074	3.51	0.000	.5491543	1.938802
Grade 12 or GED (High school graduate)	.6094098	.3511038	1.74	0.083	-.0787433	1.297563
College 1 year to 3 years (Some college or technical school)	.8970448	.3511996	2.55	0.011	.2087042	1.585385
College 4 years or more (College graduate)	.3889611	.351274	1.11	0.268	-.2995256	1.077448
Gini-Coefficient	-1.427932	.8056623	-1.77	0.076	-3.007006	.1511419
Income higher than 50,000 (ref. cat. lower than 50,000)	-3.262409	.5336357	-6.11	0.000	-4.308319	-2.216499
Interaction variable						
Higher than 50,000xGini	4.789379	1.138.319	4.21	0.000	2.558307	7.020451
Constant	7.968779	.5301058	15.03	0.000	6.929788	9.007771

Table 43. Tobit regression between number of days mental health was not good and a number of predictors with interaction variable (Higher than 50,000xGini).

Number of days mental health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Female (ref. cat. *Male*)	.9180525	.0245548	37.39	0.000	.8699258	.9661793
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.0337015	.0789875	0.43	0.670	-.1211117	.1885147
Age 30 to 34	-.0552754	.0781952	0.71	0.480	-.2085356	.0979848
Age 35 to 39	-.0948017	.0776498	-1.22	0.222	-.246993	.0573896
Age 40 to 44	-.1542178	.0781533	-1.97	0.048	-.3073959	-.0010397
Age 45 to 49	-.2822919	.07563	-3.73	0.000	-.4305244	-.1340594
Age 50 to 54	-.6035934	.0731544	-8.25	0.000	-.7469738	-.4602131
Age 55 to 59	-1.078872	.0718201	-15.02	0.000	-1.219637	-.9381066
Age 60 to 64	-1.664231	.0719937	-23.12	0.000	-1.805337	-1.523126
Age 65 to 69	-2.151334	.0750236	-28.68	0.000	-2.298378	-2.00429
Age 70 to 74	-2.567131	.0792217	-32.4	0.000	-2.722403	-2.411859
Age 75 to 79	-2.98996	.0841311	-35.54	0.000	-3.154854	-2.825066
Age 80 or older	-3.41616	.0824214	-41.45	0.000	-3.577704	-3.254617
Married (ref. cat. *Not Married*)	-.9476829	.0263539	-35.96	0.000	-.9993358	-.8960299
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-3.821805	.0892814	-42.81	0.000	-3.996794	-3.646816
Self-employed	-3.673451	.0959659	-38.28	0.000	-3.861542	-3.485361
Out of work for less than 1 year	-1.101703	.1217793	-9.05	0.000	-1.340387	-.8630195
A homemaker	-3.154316	.1029229	-30.65	0.000	-3.356042	-2.952591
A student	-3.141226	.123004	-25.54	0.000	-3.38231	-2.900142
Retired	-2.881902	.0936974	-30.76	0.000	-3.065547	-2.698258
Unable to work	3.836013	.0972329	39.45	0.000	3.645439	4.026586
Education (Ref. Cat. *Never attended*						

Number of obs	384,953
LR chi2(29)	44448.73
Prob > chi2	0.0000
Pseudo R2	0.0167

school or only kindergarten)						
Grades 1 through 8 (Elementary)	.7855466	.3599807	2.18	0.029	.0799951	1.491098
Grades 9 through 11 (Some high school)	1.21739	.354697	3.43	0.001	.5221948	1.912586
Grade 12 or GED (High school graduate)	.5193093	.3512627	1.48	0.139	-.1691551	1.207774
College 1 year to 3 years (Some college or technical school)	.7586186	.3513203	2.16	0.031	.0700412	1.447196
College 4 years or more (College graduate)	.2217898	.3513539	0.63	0.528	-.4668533	.9104329
Gini-Coefficient	.2354465	.6993566	0.34	0.736	-1.135272	1.606165
Income higher than 75,000 (ref. cat. lower than 75,000)	-2.300154	.5645675	-4.07	0.000	-3.40669	-1.193619
Interaction variable						
Higher than 75,000xGini	3.075543	1.205608	2.55	0.011	.7125878	5.438499
Constant	7.233228	.4951518	14.61	0.000	6.262746	8.203711

Table 44. Tobit regression between number of days mental health was not good and a number of predictors with interaction variable (Higher than 75,000xGini).

Appendix 12. Spillover Effect Physical Health

Number of days physical health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Female (ref. cat. *Male*)	.2080961	.0269215	7.73	0.000	.1553307	.2608615
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.5566647	.0865259	6.43	0.000	.3870764	.7262529
Age 30 to 34	.8070447	.0857167	9.42	0.000	.6390425	.9750469
Age 35 to 39	1.092718	.0851091	12.84	0.000	.9259069	1.25953
Age 40 to 44	1.346543	.0856544	15.72	0.000	1.178663	1.514423
Age 45 to 49	1.629981	.0828744	19.67	0.000	1.467549	1.792412
Age 50 to 54	1.865538	.0801674	23.27	0.000	1.708412	2.022664
Age 55 to 59	1.884051	.0787333	23.93	0.000	1.729736	2.038366
Age 60 to 64	1.640791	.0789546	20.78	0.000	1.486042	1.795539
Age 65 to 69	1.62467	.0822867	19.74	0.000	1.46339	1.785949
Age 70 to 74	1.78189	.0869236	20.50	0.000	1.611522	1.952257
Age 75 to 79	1.990593	.0924016	21.54	0.000	1.809489	2.171698
Age 80 or older	2.092594	.0905959	23.10	0.000	1.915029	2.270159
Married (ref. cat. *Not Married*)	-.5480401	.0283836	-19.31	0.000	-.6036711	-.4924091
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.232371	.0986894	-42.89	0.000	-4.4258	-4.038943
Self-employed	-4.159903	.1058363	-39.31	0.000	-4.367339	-3.952467
Out of work for less than 1 year	-1.943362	.133712	-14.53	0.000	-2.205433	-1.68129
A homemaker	-2.976905	.1133728	-26.26	0.000	-3.199112	-2.754698
A student	-3.805146	.1350099	-28.18	0.000	-4.069762	-3.540531
Retired	-2.210816	.1034024	-21.38	0.000	-2.413482	-2.00815
Unable to work	8.585832	.1068156	80.38	0.000	8.376476	8.795187
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.8009315	.3967224	2.02	0.044	.0233675	1.578496
Grades 9 through 11 (Some high school)	.7276734	.390858	1.86	0.063	-.0383966	1.493743

Number of obs	383,515
LR chi2(29)	76586.07
Prob > chi2	0.0000
Pseudo R2	0.0277

Grade 12 or GED (High school graduate)	.0319515	.3871465	0.08	0.934	-.7268441	.7907471
College 1 year to 3 years (Some college or technical school)	.130468	.3872086	0.34	0.736	-.6284492	.8893852
College 4 years or more (College graduate)	-.8382744	.3870795	-2.17	0.030	-1.596939	-.07961
Gini-Coefficient	-10.82894	2.073.022	-5.22	0.000	-14.892	-6.765882
Income higher than 15,000 (ref. cat. lower than 15,000)	-7.792059	1.025.153	-7.6	0.000	-9.801328	-5.782791
Interaction variable						
Higher than 15,000xGini	13.39436	2.173134	6.16	0.000	9.135079	17.65363
Constant	12.17335	1.059977	11.48	0.000	10.09583	14.25087

Table 45. Tobit regression between number of days physical health was not good and a number of predictors with interaction variable (Higher than 15,000xGini).

Number of days physical health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Female (ref. cat. *Male*)	.1827284	.0269169	6.79	0.000	.1299721	.2354848
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.5446554	.0864552	6.30	0.000	.3752059	.714105
Age 30 to 34	.7924389	.0856475	9.25	0.000	.6245723	.9603056
Age 35 to 39	1.084309	.0850386	12.75	0.000	.9176358	1.250982
Age 40 to 44	1.339201	.085583	15.65	0.000	1.171461	1.506942
Age 45 to 49	1.636508	.0828013	19.76	0.000	1.47422	1.798797
Age 50 to 54	1.879259	.0800958	23.46	0.000	1.722274	2.036245
Age 55 to 59	1.899267	.0786633	24.14	0.000	1.745089	2.053444
Age 60 to 64	1.649442	.0788876	20.91	0.000	1.494824	1.804059
Age 65 to 69	1.630035	.0822177	19.83	0.000	1.468891	1.791179
Age 70 to 74	1.787707	.086851	20.58	0.000	1.617482	1.957932
Age 75 to 79	1.984133	.0923236	21.49	0.000	1.803182	2.165085
Age 80 or older	2.055845	.0905207	22.71	0.000	1.878427	2.233263
Married (ref. cat. *Not Married*)	-.4338685	.0287156	-15.11	0.000	-.4901502	-.3775868
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.092043	.0986724	-41.47	0.000	-4.285437	-3.898648
Self-employed	-4.05029	.1057523	-38.3	0.000	-4.257561	-3.843019
Out of work for less than 1 year	-1.921066	.1335649	-14.38	0.000	-2.182849	-1.659283
A homemaker	-2.895704	.1132521	-25.57	0.000	-3.117674	-2.673733
A student	-3.727211	.1349222	-27.62	0.000	-3.991655	-3.462768
Retired	-2.122412	.1032982	-20.55	0.000	-2.324873	-1.91995
Unable to work	8.553656	.1067327	80.14	0.000	8.344463	8.762849
Education (Ref. Cat. *Never attended*						

Number of obs	383,515
LR chi2(29)	77226.85
Prob > chi2	0.0000
Pseudo R2	0.0280

school or only kindergarten)						
Grades 1 through 8 (Elementary)	.78386	.3963906	1.98	0.048	.0069463	1.560774
Grades 9 through 11 (Some high school)	.7549955	.3905347	1.93	0.053	-.0104408	1.520432
Grade 12 or GED (High school graduate)	.155736	.386861	0.4	0.687	-.6025001	.913972
College 1 year to 3 years (Some college or technical school)	.3114904	.3869607	0.8	0.421	-.4469411	1.069922
College 4 years or more (College graduate)	-.6025212	.3868798	-1.56	0.119	-1.360794	.1557517
Gini-Coefficient	-7.529848	1.551956	-4.85	0.000	-1.057164	-4.48806
Income higher than 20,000 (ref. cat. lower than 20,000)	-6.41755	.7983223	-8.04	0.000	-7.982238	-4.852862
Interaction variable						
Higher than 20,000xGini	10.27334	1.694389	6.06	0.000	6.952388	13.59429
Constant	10.26593	.8384992	12.24	0.000	8.622498	11.90937

Table 46. Tobit regression between number of days physical health was not good and a number of predictors with interaction variable (Higher than 20,000xGini).

Number of days physical health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Female (ref. cat. *Male*)	.1581888	.0269223	5.88	0.000	.1054219	.2109558
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.5352225	.086405	6.19	0.000	.3658713	.7045737
Age 30 to 34	.7968835	.0855949	9.31	0.000	.6291201	.9646469
Age 35 to 39	1.097218	.0849856	12.91	0.000	.930649	1.263787
Age 40 to 44	1.362654	.0855269	15.93	0.000	1.195024	1.530284
Age 45 to 49	1.672729	.0827494	20.21	0.000	1.510542	1.834915
Age 50 to 54	1.920691	.0800486	23.99	0.000	1.763799	2.077584
Age 55 to 59	1.944473	.0786193	24.73	0.000	1.790381	2.098564
Age 60 to 64	1.685049	.078844	21.37	0.000	1.530517	1.839581
Age 65 to 69	1.648042	.0821693	20.06	0.000	1.486992	1.809091
Age 70 to 74	1.785745	.0867984	20.57	0.000	1.615623	1.955867
Age 75 to 79	1.973383	.0922678	21.39	0.000	1.792541	2.154225
Age 80 or older	2.022754	.0904725	22.36	0.000	1.845431	2.200078
Married (ref. cat. *Not Married*)	-.3472347	.0289775	-11.98	0.000	-.4040297	-.2904397
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.038227	.0985379	-40.98	0.000	-4.231358	-3.845096
Self-employed	-4.020224	.1055949	-38.07	0.000	-4.227186	-3.813261
Out of work for less than 1 year	-1.942316	.1334449	-14.56	0.000	-2.203864	-1.680768
A homemaker	-2.882037	.1131036	-25.48	0.000	-3.103717	-2.660357
A student	-3.683635	.1348404	-27.32	0.000	-3.947918	-3.419352
Retired	-2.115876	.1031229	-20.52	0.000	-2.317994	-1.913758
Unable to work	8.555416	.1066635	80.21	0.000	8.346359	8.764473
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.8321555	.3961497	2.1	0.036	.0557139	1.608597

Number of obs	383,515
LR chi2(29)	77689.61
Prob > chi2	0.0000
Pseudo R2	0.0281

Grades 9 through 11 (Some high school)	.8135484	.3903097	2.08	0.037	.048553	1.578544
Grade 12 or GED (High school graduate)	.2392101	.3866535	0.62	0.536	-.5186192	.9970394
College 1 year to 3 years (Some college or technical school)	.4462249	.386786	1.15	0.249	-.3118642	1.204314
College 4 years or more (College graduate)	-.3863477	.3867823	-1.00	0.318	-1.14443	.3717342
Gini-Coefficient	-4.794427	1.24592	-3.85	0.000	-7.236392	-2.352461
Income higher than 25,000 (ref. cat. lower than 25,000)	-5.198609	.676789	-7.68	0.000	-6.525095	-3.872123
Interaction variable						
Higher than 25,000xGini	7.683993	1.438996	5.34	0.000	4.863604	10.50438
Constant	8.606128	.7154006	12.03	0.000	7.203964	10.00829

Table 47. Tobit regression between number of days physical health was not good and a number of predictors with interaction variable (Higher than 25,000xGini).

Number of days physical health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Female (ref. cat. *Male*)	.1498803	.0269325	5.57	0.000	.0970935	.2026671
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.4979084	.0864138	5.76	0.000	.32854	.6672768
Age 30 to 34	.7988464	.0855916	9.33	0.000	.6310894	.9666033
Age 35 to 39	1.115558	.0849818	13.13	0.000	.9489964	1.28212
Age 40 to 44	1.393728	.0855244	16.30	0.000	1.226103	1.561354
Age 45 to 49	1.712644	.0827543	20.70	0.000	1.550448	187484
Age 50 to 54	1.954925	.0800554	24.42	0.000	1.798019	2.111831
Age 55 to 59	1.975449	.0786261	25.12	0.000	1.821344	2.129553
Age 60 to 64	1.700272	.0788458	21.56	0.000	1.545737	1.854808
Age 65 to 69	1.639898	.0821658	19.96	0.000	1.478855	1.80094
Age 70 to 74	1.764459	.0867956	20.33	0.000	1.594343	1.934576
Age 75 to 79	1.930462	.0922705	20.92	0.000	1.749615	2.111309
Age 80 or older	1.972218	.0904905	21.79	0.000	1.794859	2.149576
Married (ref. cat. *Not Married*)	-.3072711	.0292129	-10,52	0.000	-.3645275	-.2500148
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.094524	.0983494	-41,63	0.000	-4.287286	-3.901762
Self-employed	-4.070761	.1054639	-38,6	0.000	-4.277467	-3.864055
Out of work for less than 1 year	-1.974232	.1334178	-14,8	0.000	-2.235727	-1.712737
A homemaker	-2.938206	.1129989	-26	0.000	-3.15968	-2.716731
A student	-3.681319	.1348259	-27,3	0.000	-3.945573	-3.417064
Retired	-2.189096	.1029736	-21,26	0.000	-2.390921	-1.987271
Unable to work	8.583696	.1066511	80.48	0.000	8.374663	8.792729
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.8763212	.3961382	2.21	0.027	.0999021	1.65274

Number of obs	383,515
LR chi2(29)	77716.52
Prob > chi2	0.0000
Pseudo R2	0.0281

Grades 9 through 11 (Some high school)	.8441317	.3903041	2.16	0.031	.0791474	1.609116
Grade 12 or GED (High school graduate)	.229004	.3866301	0.59	0.554	-.5287794	.9867874
College 1 year to 3 years (Some college or technical school)	.4551616	.3867723	1.18	0.239	-.3029007	1.213224
College 4 years or more (College graduate)	-.301791	.386845	0,78	0.435	-1.059996	.4564136
Gini-Coefficient	-1.667099	1.045507	-1,59	0.111	-3.716261	.3820641
Income higher than 35,000 (ref. cat. lower than 35,000)	-3.43173	.6117763	-5,61	0.000	-4.630793	-2.232667
Interaction variable						
Higher than 35,000xGini	4.136786	1.302796	3.18	0.001	1.583344	6.690228
Constant	6.896478	.6396135	10.78	0.000	5.642855	8.150102

Table 48. Tobit regression between number of days physical health was not good and a number of predictors with interaction variable (Higher than 35,000xGini).

Number of days physical health was not good.	Coef.	Std. Err.	T	P>t	[95% Conf.	Interval]
Female (ref. cat. *Male*)	.167343	.0269369	6.21	0.000	.1145475	.2201385
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.4714659	.0864881	5.45	0.000	.3019518	.6409801
Age 30 to 34	.8040745	.0856439	9.39	0.000	.636215	.971934
Age 35 to 39	1.138942	.0850339	13.39	0.000	.9722779	1.305.606
Age 40 to 44	1.423851	.0855824	16.64	0.000	1.256112	1.59159
Age 45 to 49	1.734631	.0828174	20.95	0.000	1.572311	1.89695
Age 50 to 54	1.978745	.08012	24.70	0.000	1.821712	2.135778
Age 55 to 59	1.98659	.0786838	25.25	0.000	1.832372	2.140808
Age 60 to 64	1.694209	.0788938	21.47	0.000	1.539579	1.848838
Age 65 to 69	1.623747	.0822151	19.75	0.000	1.462608	1.784886
Age 70 to 74	1.746461	.0868504	20.11	0.000	1.576237	1.916686
Age 75 to 79	1.920229	.0923317	20.80	0.000	1.739261	2.101196
Age 80 or older	1.987178	.0905443	21.95	0.000	1.809714	2.164642
Married (ref. cat. *Not Married*)	-.353316	.0292497	-12.08	0.000	-.4106446	-.2959874
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.257908	.0981379	-43.39	0.000	-4.450256	-4.065561
Self-employed	-4.215178	.1053385	-40.02	0.000	-4.421638	-4.008717
Out of work for less than 1 year	-2.038171	.1334758	-15.27	0.000	-2.299779	-1.776562
A homemaker	-3.061199	.1129468	-27.10	0.000	-3.282571	-2.839827
A student	-3.749354	.1348708	-27.80	0.000	-4.013696	-3.485011
Retired	-2.343933	.1028635	-22.79	0.000	-2.545542	-2.142324
Unable to work	8.604907	.1067127	80.64	0.000	8.395753	8.81406
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.868517	.3963788	2.19	0.028	.0916264	1.645408

Number of obs	383,515
LR chi2(29)	77248.39
Prob > chi2	0.0000
Pseudo R2	0.0280

Grades 9 through 11 (Some high school)	.7822934	.3905302	2.00	0.045	.0168659	1.547721
Grade 12 or GED (High school graduate)	.0559778	.3867941	0.14	0.885	-.7021271	.8140827
College 1 year to 3 years (Some college or technical school)	.2488109	.3868961	0.64	0.520	-.5094939	1.007116
College 4 years or more (College graduate)	-.4791887	.3869828	-1.24	0.216	-1.237663	.2792862
Gini-Coefficient	.0035833	.8846886	0.00	0.997	-1.73038	1.737547
Income higher than 50,000 (ref. cat. lower than 50,000)	-2.463233	.5853616	-4.21	0.000	-3.610.525	-1.315942
Interaction variable						
Higher than 50,000xGini	2.560513	1.248677	2.05	0.040	.1131429	5.007884
Constant	6.107295	.5827101	10.48	0.000	4.965201	7.249389

Table 49. Tobit regression between number of days physical health was not good and a number of predictors with interaction variable (Higher than 50,000xGini).

Number of days physical health was not good.	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Female (ref. cat. *Male*)	.1894043	.0269447	7.03	0.000	.1365935	.2422151
Age (ref. cat. *Age 18 to 24*)						
Age 25 to 29	.4698529	.0865834	5.43	0.000	.3001521	.6395537
Age 30 to 34	.7930023	.0857184	9.25	0.000	.6249968	.9610078
Age 35 to 39	1.138708	.0850996	13.38	0.000	.9719152	1.305501
Age 40 to 44	1.429658	.0856573	16.69	0.000	1.261772	1.597544
Age 45 to 49	1.730122	.0828921	20.87	0.000	1.567656	1.892588
Age 50 to 54	1.962282	.0801852	24.47	0.000	1.805121	2.119443
Age 55 to 59	1.957843	.078738	24.87	0.000	1.803519	2.112167
Age 60 to 64	1.66643	.0789505	21.11	0.000	1.51169	1.821171
Age 65 to 69	1.608039	.082283	19.54	0.000	1.446.767	1.769311
Age 70 to 74	1.744248	.0869223	20.07	0.000	1.573882	1.914613
Age 75 to 79	1.934478	.0924048	20.93	0.000	1.753367	2.115589
Age 80 or older	2.035675	.0905988	22.47	0.000	1.858104	2.213246
Married (ref. cat. *Not Married*)	-.4683937	.0289257	-16.19	0.000	-.5250873	-.4117002
Employment (ref. cat. *Out of work for 1 year or more*)						
Employed for wages	-4.419268	.0980014	-45.09	0.000	-4.611348	-4.227188
Self-employed	-4.332085	.1053187	-41.13	0.000	-4.538506	-4.125663
Out of work for less than 1 year	-2.080177	.1335741	-15.57	0.000	-2.341979	-1.818376
A homemaker	-3.158246	.112971	-27.96	0.000	-3.379666	-2.936826
A student	-3.834363	.1349392	-28.42	0.000	-4.09884	-3.569886
Retired	-2.459138	.1028622	-23.91	0.000	-2.660745	-2.257531
Unable to work	8.628909	.1067947	80.8	0.000	8.419594	8.838223
Education (Ref. Cat. *Never attended school or only kindergarten)*						
Grades 1 through 8 (Elementary)	.8715588	.3966972	2.2	0.028	.0940441	1.649073

Number of obs	383,515
LR chi2(29)	76632.72
Prob > chi2	0.0000
Pseudo R2	0.0277

Grades 9 through 11 (Some high school)	.7374853	.3908366	1.89	0.059	-.0285428	1.503513
Grade 12 or GED (High school graduate)	-.0711942	.3870648	0.18	0.854	-.8298296	.6874413
College 1 year to 3 years (Some college or technical school)	.0582939	.3871239	0.15	0.880	-.7004573	.8170451
College 4 years or more (College graduate)	-.7153626	.3871634	-1.85	0.065	-1.474.191	.0434662
Gini-Coefficient	1.328816	.7678855	1.73	0.084	-.1762169	2.833848
Income higher than 75,000 (ref. cat. lower than 75,000)	-1.46927	.6190246	-2.37	0.018	-2.68254	-.2560001
Interaction variable						
Higher than 75,000xGini	.9504189	1.321912	0.72	0.472	-1.640489	3.541327
Constant	5.558197	.5444808	10.21	0.000	4.491031	6.625363

Table 50. Tobit regression between number of days physical health was not good and a number of predictors with interaction variable (Higher than 75,000xGini).

Appendix 13. Syntax Multilevel Analysis

<u>500 Cities Project County Level: Adding Gini</u>

Gen GiniCity=0

replace Gini City = 0.4307 if (city==1)

replace Gini City = 0.3982 if (city==2)

replace Gini City = 0.4429 if (city==3)

replace Gini City = 0.4609 if (city==4)

replace Gini City = 0.4264 if (city==5)

replace Gini City = 0.4436 if (city==6)

replace Gini City = 0.5010 if (city==7)

replace Gini City = 0.4013 if (city==8)

replace Gini City = 0.3910 if (city==9)

replace Gini City = 0.5484 if (city==10)

replace Gini City = 0.4455 if (city==11)

replace Gini City = 0.3998 if (city==12)

replace Gini City = 0.4393 if (city==13)

replace Gini City = 0.4637 if (city==14)

<u>500 Cities Project State Level: Adding Gini</u>

gen GiniCounty=0

replace Gini County = 0.4604 if (county==1)

replace Gini County = 0.5030 if (county==2)

replace Gini County = 0.4695 if (county==3)

replace Gini County = 0.4596 if (county==4)

replace Gini County = 0.4400 if (county==5)

replace Gini County = 0.4644 if (county==6)

replace Gini County = 0.4644 if (county==7)

replace Gini County = 0.4888 if (county==8)

replace Gini County = 0.4649 if (county==9)

replace Gini County = 0.4910 if (county==10) replace Gini County = 0.4559 if (county==11)

replace Gini County = 0.4821 if (county==12)

replace Gini County = 0.4340 if (county==13)

replace Gini County = 0.4466 if (county==14)

replace Gini County = 0.4969 if (county==15)

replace Gini County = 0.4645 if (county==16)

replace Gini County = 0.4532 if (county==17)

replace Gini County = 0.4641 if (county==18)

replace Gini County = 0.4474 if (county==19)

replace Gini County = 0.4655 if (county==20)

replace Gini County = 0.4571 if (county==21)

replace Gini County = 0.4514 if (county==22)

replace Gini County = 0.5029 if (county==23)

replace Gini County = 0.4707 if (county==24)

replace Gini County = 0.4481 if (county==25)

replace Gini County = 0.4554 if (county==26)

<u>500 Cities Project Country Level: Adding Gini:</u>

gen GiniState=0

replace GiniState=0.4081 if (state_N3==1)

replace GiniState=0.4847 if (state_N3==2)

replace GiniState=0.4719 if (state_N3==3)

replace GiniState=0.4713 if (state_N3==4)

replace GiniState=0.4899 if (state_N3==5)

replace GiniState=0.4586 if (state_N3==6)

replace GiniState=0.4945 if (state_N3==7)

replace GiniState=0.4522 if (state_N3==9)

replace GiniState=0.4852 if (state_N3==10)

replace GiniState=0.4813 if (state_N3==11)

```
replace GiniState=0.4420 if (state_N3==12)
replace GiniState=0.4451 if (state_N3==13)
replace GiniState=0.4503 if (state_N3==14)
replace GiniState=0.4810 if (state_N3==15)
replace GiniState=0.4527 if (state_N3==16)
replace GiniState=0.4550 if (state_N3==17)
replace GiniState=0.4813 if (state_N3==18)
replace GiniState=0.4990 if (state_N3==19)
replace GiniState=0.4786 if (state_N3==20)
replace GiniState=0.4499 if (state_N3==21)
replace GiniState=0.4519 if (state_N3==22)
replace GiniState=0.4695 if (state_N3==23)
replace GiniState=0.4496 if (state_N3==24)
replace GiniState=0.4646 if (state_N3==25)
replace GiniState=0.4828 if (state_N3==26)
replace GiniState=0.4667 if (state_N3==27)
replace GiniState=0.4780 if (state_N3==28)
replace GiniState=0.4533 if (state_N3==29)
replace GiniState=0.4477 if (state_N3==30)
replace GiniState=0.4304 if (state_N3==31)
replace GiniState=0.4813 if (state_N3==32)
replace GiniState=0.4796 if (state_N3==33)
replace GiniState=0.4577 if (state_N3==34)
replace GiniState=0.5129 if (state_N3==35)
replace GiniState=0.4680 if (state_N3==36)
replace GiniState=0.4645 if (state_N3==37)
replace GiniState=0.4583 if (state_N3==38)
replace GiniState=0.4689 if (state_N3==39)
replace GiniState=0.4781 if (state_N3==40)
replace GiniState=0.4735 if (state_N3==41)
replace GiniState=0.4495 if (state_N3==42)
```

replace GiniState=0.4790 if (state_N3==43)

replace GiniState=0.4800 if (state_N3==44)

replace GiniState=0.4263 if (state_N3==45)

replace GiniState=0.4705 if (state_N3==46)

replace GiniState=0.4539 if (state_N3==47)

replace GiniState=0.4591 if (state_N3==48)

replace GiniState=0.4498 if (state_N3==49)

replace GiniState=0.4711 if (state_N3==50)

replace GiniState=0.4360 if (state_N3==51)

<u>Changing variable to natural log of variable</u>

histogram MHLTH_CrudePrev

gen lnMHLTH = ln(MHLTH_CrudePrev)

histogram lnMHLTH

histogram PHLTH_CrudePrev

gen lnPHLTH = ln(PHLTH_CrudePrev)

histogram lnPHLTH

<u>Adding variables from US Census</u>

Note: Not all these syntaxes are saved, but one example of a syntax that shows how a variable is added from the US Census to the 500 Cities Project, is given. This way of adding a variable is applied is for every variable from the US Census:

import excel "C:\Users\Gebruiker\Documents\(Un)Employment USA.xlsx", sheet("ACS_16_5YR_S

ren A TractFIPS

label variable TractFIPS "TractFIPS"

drop D

drop E

destring B C, generate(laborforce unemp) force

drop C B

merge m:m TractFIPS using "C:\Users\Gebruiker\Documents\unempus.dta", nogenerate

Analyses at County Level:

reg lnMHLTH GiniCity medincome grossrent laborforce unemp hischool belowpov Gini2

mixed lnMHLTH || city:

estat icc

mixed lnMHLTH GiniCity medincome grossrent laborforce unemp hischool belowpov Gini2 || city:

estat icc

reg lnPHLTH GiniCity medincome grossrent laborforce unemp hischool belowpov Gini2

mixed lnPHLTH || city:

estat icc

mixed lnPHLTH GiniCity medincome grossrent laborforce unemp hischool belowpov Gini2 ||

city:

Estat icc

Analyses at State Level:

reg lnMHLTH GiniCounty medincome grossrent laborforce unemp hischool belowpov Gini2

mixed lnMHLTH || county:

estat icc

mixed lnMHLTH GiniCounty medincome grossrent laborforce unemp hischool belowpov Gini2 || county:

estat icc

reg lnPHLTH GiniCounty medincome grossrent laborforce unemp hischool belowpov Gini2

mixed lnPHLTH || county:

estat icc

mixed lnPHLTH GiniCounty medincome grossrent laborforce unemp hischool belowpov Gini2 ||

county:

Estat icc

Analyses at Country Level:

reg lnMHLTH GiniState medincome grossrent laborforce unemp hischool belowpov Gini2

mixed lnMHLTH || state:

estat icc

mixed lnMHLTH GiniState medincome grossrent laborforce unemp hischool belowpov Gini2 || state_N3:

estat icc

reg lnPHLTH GiniState medincome grossrent laborforce unemp hischool belowpov Gini2

mixed lnPHLTH || state:

estat icc

mixed lnPHLTH GiniState medincome grossrent laborforce unemp hischool belowpov Gini2 ||

state:

Estat icc

Appendix 14. Syntax Spillover Effect Analysis

<u>BRFSS: Adding Gini</u>

```
gen gini=.
replace gini=0.4847 if ( _state==1)
replace gini=0.4081 if ( _state==2)
replace gini=0.4713 if ( _state==4)
replace gini=0.4719 if ( _state==5)
replace gini=0.4899 if ( _state==6)
replace gini=0.4586 if ( _state==8)
replace gini =0.4945 if ( _state==9)
replace gini=0.4522 if ( _state==10)
replace gini=0.4852 if ( _state==12)
replace gini=0.4813 if ( _state==13)
replace gini=0.4420 if ( _state==15)
replace gini=0.4503 if ( _state==16)
replace gini=0.4810 if ( _state==17)
replace gini=0.4527 if ( _state==18)
replace gini=0.4451 if ( _state==19)
 replace gini=0.4550 if ( _state==20)
replace gini=0.4813 if ( _state ==21)
replace gini=0.4990 if ( _state==22)
replace gini=0.4786 if ( _state==25)
replace gini=0.4499 if ( _state==24)
replace gini=0.4519 if ( _state==23)
replace gini=0.4695 if ( _state==26)
replace gini=0.4496 if ( _state==27)
replace gini=0.4828 if ( _state==28)
replace gini=0.4646 if ( _state==29)
replace gini=0.4667 if ( _state==30)
replace gini=0.4780 if ( _state==37)
```

```
replace gini=0.4533 if ( _state==38)
replace gini=0.4477 if ( _state==31)
replace gini=0.4304 if ( _state==33)
replace gini=0.4813 if ( _state==34)
replace gini=0.4769 if ( _state==35)
replace gini=0.4577 if ( _state==32)
replace gini=0.5129 if ( _state==36)
replace gini=0.4680 if ( _state==39)
replace gini=0.4645 if ( _state==40)
replace gini=0.4583 if ( _state==41)
replace gini=0.4689 if ( _state==42)
replace gini=0.4781 if ( _state==44)
replace gini=0.4735 if ( _state==45)
replace gini=0.4495 if ( _state==46)
replace gini=0.4790 if ( _state==47)
replace gini=0.4800 if ( _state==48)
replace gini=0.4263 if ( _state==49)
replace gini=0.4705 if ( _state==51)
replace gini=0.4539 if ( _state==50)
replace gini=0.4591 if ( _state==53)
replace gini=0.4498 if ( _state==55)
replace gini=0.4711 if ( _state==54)
replace gini=0.4360 if ( _state==56)
```

Creating Binary Dummy Variables

```
gen lowhigh15000=.
replace lowhigh15000=0 if (income2<=2)
replace lowhigh15000=1 if ( income2 >2)
replace lowhigh15000=. if ( income2 >10)
```

gen lowhigh20000=.

replace lowhigh20000=0 if (income2<=3)

replace lowhigh20000=1 if (income2>3)

replace lowhigh20000=. if (income2>9)

gen lowhigh25000=.

replace lowhigh25000=0 if (income2<=4)

replace lowhigh25000=1 if (income2>4)

replace lowhigh25000=. if (income2>9)

gen lowhigh35000=.

replace lowhigh35000=0 if (income2<=5)

replace lowhigh35000=1 if (income2>5)

replace lowhigh35000=. if (income2>9)

gen lowhigh50000=.

replace lowhigh50000=0 if (income2<=6)

replace lowhigh50000=1 if (income2>6)

replace lowhigh50000=. if (income2>9)

gen lowhigh75000=.

replace lowhigh75000=0 if (income2<=7)

replace lowhigh75000=1 if (income2>7)

replace lowhigh75000=. if (income2>9)

<u>Changing meaningless data to missing data.</u>

replace menthlth = 0 if (menthlth==88)

replace menthlth = . if (menthlth==77)

replace menthlth = . if (menthlth==99)

replace physhlth = 0 if (physhlth==88)

replace physhlth = . if (physhlth==77)

```
replace physhlth = . if (physhlth==99)
replace income2 =. if (income2==77)
replace income2 =. if (income2==99)
replace _ageg5yr =. if (_ageg5yr==14)
replace sex =. if (sex==9)
replace _state =. if (_state==66)
replace _state =. if (_state==72)
replace _state=. if (_state==78)
replace employ =. if (employ==9)
replace educa =. if (educa==9)
```

Adding Time Variables

```
merge m:m _state using "C:\Users\Gebruiker\Documents\Ginistaat.dta"
generate ginichange5yr = gini-gini2011
merge m:m _state using "C:\Users\Gebruiker\Documents\gini2006.dta"
generate ginichange10yr = gini-gini2006
```

Reference Categories:

```
fvset base 5 marital
fvset base 3 employ1
```

Analyses:

```
tobit menthlth i._state
tobit physhlth i._state
tobit menthlth i._state i.sex i._ageg5yr i.married i.employ1 i.educa
tobit physhlth i._state i.sex i._ageg5yr i.married i.employ1 i.educa
tobit menthlth gini i.sex i._ageg5yr i.married i.employ1 i.educa
tobit physhlth gini i.sex i._ageg5yr i.married i.employ1 i.educa
tobit menthlth gini i.sex i._ageg5yr i.married i.employ1 i.educa ginichange5yr
tobit physhlth gini i.sex i._ageg5yr i.married i.employ1 i.educa ginichange10yr
```

```
tobit menthlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh15000
tobit menthlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh20000
tobit menthlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh25000
tobit menthlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh35000
tobit menthlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh50000
tobit menthlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh75000
tobit physhlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh15000
tobit physhlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh20000
tobit physhlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh25000
tobit physhlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh35000
tobit physhlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh50000
tobit physhlth i.sex i._ageg5yr i.married i.employ1 i.educa c.gini##lowhigh75000
```