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Moving Towards Health: An Investigative Study on Movers Across the United States

Author: Claudia Alexandra Duarte (502725)

Supervisor: Joaquim Vidiella Martin

Second Assessor: Pieter Bakx

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Preface

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics, or Erasmus University Rotterdam.

Abstract

The causal effects of an individuals surrounding area, or neighborhood, on their health outcomes continue to pose difficult to measure, yet geographical health disparities are rife across the globe. This paper uses longitudinal data of movers across the United States to investigate the relationship between an individual's exposure to a region of residence and their health outcomes; considering both self-reported and physical health measures through the application of fixed-effects regression analysis. Four health measures are considered including Self-Reported Health, Body Mass Index, Pulmonary Function, and Pulse. The data utilized within this paper consists of two distinct data sets, including the RAND HRS Longitudinal File 2018 in combination with the Cross-Wave Census Region/Division and Mobility File. Additionally, this paper considers three (un)healthy behaviors, including alcohol consumption, exercise frequency, and smoking status, and studies these behaviors across individuals around the time of their move to add depth to the primary results, enabling us to better understand if subsequent changes in individual health outcomes are potentially driven by changes in behavior triggered by their new region of residence. Results show that individuals who moved to a better environment were approximately 9.6%, and 7.2% more likely to report themselves as having good Self-Reported Health one period, and two periods after moving respectively. There is no evidence to suggest that individuals who move to a worse environment, experience any changes in their Self-Reported Health. Furthermore, neither were there any subsequent changes in physical health measures, regardless of whether individuals moved to a better or worse environment.

Key words: Neighbourhood effects, health outcomes, self-reported health, BMI, pulmonary function, pulse, behavior, healthy habits, health inequities, health disparities, and geographical variation.

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1 Introduction

Average life expectancies vary drastically across the globe. In a recent paper, Freeman et al. (2020) highlighted that the average life expectancy ranges from 52 years old in Sierra Leone and the Central African Republic to 84 years in Japan and Hong Kong - an astounding 32 year gap. Notably, these disparities are not just present across continents. Chetty et al. (2016b) estimated that life expectancy at age 40 ranged all the way from 85 years old in San Jose, California to 81 years old in Las Vegas, Nevada. This indicates that disparities in life expectancies is not just an issue globally, but also within countries themselves, and particularly within the US.

The US boasts the highest level of healthcare expenditures in the world, and currently sits at $10,921, per capita per annum, according to World Bank data (World Health Organization Global Health Expenditure database, 2022). This provides an estimate of expenditures, including all healthcare goods and services consumed during each year. In 2019, the US federal government spent approximately $1.2 trillion on healthcare aggregately (Congressional Budget Office (2020a); Congressional Budget Office (2020b); Joint Committee on Taxation (2020); Office of Management and Budget (2020)). These $1.2 trillion can be broadly grouped into three consumption streams. The first and largest is Medicare,[1] which claimed around $644 billion, followed closely by Medicaid[2] which claimed close to $427 billion, leaving $80 billion to be claimed by veterans' medical care (Congressional Budget Office (2020a); Congressional Budget Office (2020b); Joint Committee on Taxation (2020); Office of Management and Budget (2020)). However, despite high levels of healthcare expenditure, the US still illustrates high income-based disparities in both health outcomes and accessibility to healthcare. In fact, the gap in life expectancy between the richest 1% of Americans and the poorest 1% of Americans has continued to widen since the 1970s, and currently stands at a staggering 10.1 years for women and 14.6 years for their male counterparts (Dickman et al. (2017)). Regardless of the efforts and funds channeled into Medicare, Medicaid, and military healthcare, inequalities in accessibility to healthcare are largely due to high rates of uninsurance, or underinsurance, amongst individuals with lower incomes (Dickman et al. (2017)). Explicitly, it was recorded that in 2020 31.6 million individuals, 9.7% of the American population had no health insurance of any kind (AE and RA (2022)). This highlights the financial and political importance of understanding such income-based health disparities and their root causes.

The observed geographic variation in health outcomes could be driven by two distinct sources. One possible driver is that an individual's area of residence may have causal effects on their health outcomes – suggesting that after relocating an individual may experience subsequent changes in their health due to place effects. However, another potential driver is that the geographical variation in health is due to

[1] For those unfamiliar with the federal social insurance program, offered in the US, Medicare is federal health insurance for individuals aged sixty-five or older.

[2] Medicaid provides health coverage to eligible individuals, who require additional support, such as low-income adults, children, pregnant women, the elderly, and individuals with disabilities. This makes Medicaid one of the largest means-tested programs in the US (Sommers & Oellerich, 2013). Medicaid's primary focus has typically been described as providing a framework through which access to healthcare, and potentially health outcomes, can be improved for those individuals who need it the most. However, after the 2008 financial crisis, the poverty-reducing effects of the Medicaid program started to gather the interest of increasing numbers of researchers (Sommers & Oellerich, 2013).

underlying systematic differences in the populations living in each area - for example, demographics, lifestyle, and other dietary and exercise habits. Selection effects refer to the fact that individuals have the tendency to select themselves into particular areas. For example, individuals who value an active lifestyle are probably more likely to move to easily walkable areas, whilst less active individuals may be more likely to move to auto-dependent areas (Arcaya et al. (2015)). Selection effects are likely to be partly caused by certain unobservable characteristics that individuals possess, which are difficult to control for, which in turn makes drawing causal inferences and informing policy from simple linear regressions more troublesome. Therefore, a new challenge of disentangling the two, causal place effects and selection effects, arises. This paper aims to add to the growing body of literature which tackles the challenge of disentangling causal place effects and selection effects, in order to better understand the effects of an individual's area of residence on their health outcomes and thereby motivating the following research questions and sub-questions:

- RQ1 To what extent does exposure to a better (or worse) environment have beneficial (or negative) effects on an individual's overall health?
  - RQ1.1 Does exposure to a better (or worse) environment result in an improvement (or deterioration) of individual Self-Reported Health?
  - RQ1.2 Are improvements in Self-Reported Health indicative of trends in physical health measures specifically, BMI, Pulmonary Function, and Pulse?
- RQ2 To what extent can the subsequent improvements (or decreases) in physical health measures be explained by behavioral changes triggered by a good (or bad) move?

In previous literature, papers have attempted to unravel the two effects through the application of various methodological approaches. A review of multilevel analysis studies on neighborhood influences on health, Kawachi and Subramanian (2007), summarised three key approaches. Specifically, the use of instrumental variable estimation, propensity score matching, and finally, what is often regarded as the gold standard for estimating causal effects, randomized control trials (Kawachi and Subramanian (2007)). These approaches have led to both quasi-experimental and experimental evidence in this field of research. For example, the evacuations of residents to a multitude of different neighborhoods after the wake of a natural disaster would provide a perfect instrumental variable and quasi-experimental setting. Provided, that the location of destination neighborhoods was a matter of random lottery. Sacerdote (2012) followed a similar approach when he examined the long-term academic performance of students affected by Hurricane Katrina and Rita and found that three to four years after the disaster evacuees displaced from New Orleans saw a 0.18 standard deviation improvement in their test scores. These findings even led Arne Duncan, the US Secretary of Education, to say "I think the best thing that happened to the education system in New Orleans was Hurricane Katrina" (Sacerdote (2012)). Alongside this, there is a promising branch of literature that explores the experimental evidence collected from the Moving To Opportunity (MTO) experiment. The MTO experiment offered randomly selected families who were living in high-poverty neighborhoods housing vouchers which enabled them to move to lower-poverty neighborhoods (Chetty et al. (2016a)). Specifically, Turney et al. (2013) found positive causal effects of moving to a low-poverty neighborhood on adult mental health - even when controlling for additional stress factors, most of which were associated with the procedure of moving.

Whilst experimental evidence can provide invaluable insights regarding the effect of one's neighborhood on their overall level of health, it is unfortunately scarce and exceedingly difficult to implement. For example, whilst it may seem needless to clarify, it is imperative that we keep in mind that randomly moving individuals to different states across the US is both unethical and extremely challenging to implement. This leaves us reliant on other, quasi-experimental, methods. Two exceptions, however, include the MTO experiment and studies investigating the progression of asylum seekers' health status after relocating elsewhere. Grönqvist et al. (2012) followed a similar approach when they investigated the probability of refugees being hospitalized at least once in the five years following their arrival to their first area of residence, Swedish refugee placement policy coupled with comprehensive hospitalization administrative data made this possible. Whilst this is a seemingly sound alternative to experimental evidence, as the relocation of asylum seekers provides us with some degree of exogenous variation which can be exploited, it is nevertheless imperative to acknowledge that asylum seekers consist of a group of individuals in a very irregular situation which is not easily generalizable to the average individual. As a result, these studies are limited by their external validity, similar to the MTO experiment – which also does not represent a situation in which an average individual would typically find themselves in. It is precisely because of this limitation that investigating movers provides a useful opportunity to collate quasi-experimental evidence. Specifically, movers represent a sub-section of the population that should, on average, be representative of the wider population. However, while studying movers allows for a unique opportunity to unravel the causal effect of areas of residence on health outcomes, another problem arises from this: the choice to move. Because moving is an endogenous choice, naïve comparisons of outcomes of individuals who choose to move to different areas confound the causal effects of one's local area with selection effects (Chetty et al. (2016a)). Despite this, one is still able to estimate the causal effects of neighborhood exposure through exploiting variation in the time of move across individuals and the subsequent length of exposure, as was done in previous works such as Chetty et al. (2016a).

A systematic literature review, published by Arcaya et al. (2016), expressed that interest in the topic of neighborhood effects on health has grown rapidly over the past twenty years. The growth of research in this field, is perhaps due to the realization of policymakers and researcher's that their goals regarding public health should not be solely focused on improving overall population health, but also on reducing differences in health based on geography, ethnicity, socio-economic status, and other social factors (Arcaya et al. (2015)). Previous literature has provided strong cases for neighborhood effects on a variety of different health outcomes such as depression, mental health, early childhood health outcomes, birth outcomes, all-cause mortality as well as other general health outcomes (Arcaya et al. (2016)). However, they do criticize the existing body of literature on neighborhood effects on health and encourage diversity in further research, highlighting the lack of longitudinal and quasi-experimental or entirely experimental research in this area. In addition to this, they stress that the most frequently investigated health outcome was Body Mass Index (BMI) and/or obesity which replaced mental health as the most investigated outcome in the year 2010 (Arcaya et al. (2016)).

This paper is primarily interested in unraveling the effects of one's local area on their health outcomes, by exploiting individuals' choice to move across geographical areas within the United States. The contribution of this study to the existing literature is twofold. First, the study is longitudinal in nature which, as previously mentioned, is something that is lacking among studies investigating the effects of neighborhood exposure on health. Concretely, the study is longitudinal as it follows the progression of mover's health states over a six-year period. Another point highlighted in the systematic literature review, by Arcaya et al. (2016), was a substantial focus on estimating neighborhood exposure effects on BMI and/or obesity as a health outcome of choice. Therefore, whilst this paper does choose BMI as one outcome variable, to provide a metric to compare against existing results, it also proposes three novel outcome variables – specifically, blood pressure, pulmonary functionality, and self-reported health.

This paper finds that individuals who moved to a better environment, with lower levels of income inequality, were approximately 9.6%, and 7.2% more likely to report themselves as having good Self-Reported Health two years, and four years after moving respectively. There is no evidence however to suggest that individuals who move to a worse environment, with higher levels of income inequality, experience any changes in their Self-Reported Health. Furthermore, neither were there any subsequent changes in the physical health measures investigated (BMI, Pulmonary Function, and Pulse), regardless of whether individuals moved to a better, or worse, environment. This is in line with the findings of Fiscella and Franks (2000), which found that whilst income inequality does appear to have small effects on self-reported health it does not appear to have any effect on mortality. In addition to this, it is explained in Fiscella and Franks (2000) that the effects of income inequality are mediated predominantly through psychological pathways rather than bio-medical pathways, which provides an explanation for why there was no evidence supporting subsequent changes in individuals' physical health measures, irrespective of where they moved to. Furthermore, this finding is corroborated by the findings of several other studies, which illustrate that populations belonging to more equal societies ultimately see better health outcomes on average (Lynch et al. (2004); Macinko et al. (2003); Wagstaff and Van Doorslaer (2000)). However, although the direction of the effect appears to be widely accepted, the magnitude of it appears to remain somewhat unclear. For example, whilst Fiscella and Franks (2000) reports income inequality to have a small effect on self-reported health, which is in line with the results presented throughout this paper, other studies have found much more sizeable effects. For example, Shi and Starfield (2000) found that individuals living in states with lower levels of income inequality were anywhere between 1.2 to 1.3 times more likely to report themselves as having good or excellent health, in comparison to those living in states with higher levels of income inequality.

2 Background & Theoretical Framework

2.1 Background

Throughout this paper, nine geographical divisions of the United States are considered. Namely, the Census Bureau-designated regions and divisions. Whereby, the United States is categorized into four regions: The Northeast, Midwest, South, and West Regions. Within the four regions, each region consists of two to three divisions which are made up of anywhere between three to nine states. Where division five, the South Atlantic division, in the South Region consists of the most states at a total of nine including Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, Washington D.C., and West Virginia. Whilst the Middle Atlantic division, division two, in the Northeast Region consists of the least number of states including only New Jersey, New York, and Pennsylvania. The four regions, their nested nine divisions, and included states are outlined in Table 1 below. The Census Bureau-designated regions and divisions were defined as early as the 1950s by the United States Census Bureau, and have been widely used for data collection and analysis ever since (Bradburn et al. (2004)). Whilst the Census Bureau-designated regions and divisions are large, larger than alternatives used in similar strands of literature such as zip code areas which are touched upon briefly below, they are relevant regardless. The primary reason for this is that data on health outcomes, at an individual level, is relatively poor, thus using larger regions allows us to study the effects of an individual's region on their health outcomes. Nonetheless, this limitation is addressed later and discussed in further detail in the Discussion & Conclusion section.

In previous literature where neighborhood effects on health outcomes, and other outcome variables such as intergenerational mobility, were analyzed researchers have typically chosen to focus on a commuting zone or zip code level. For example, the work of Chetty and Hendren (2018), found that children growing up in low-income families experienced increases in income in their adulthood of 0.5% for each year of childhood exposure to one standard deviation better county. In their research, Chetty and Hendren (2018) looked at differences across commuting zones, commuting zones were created in 1990 with the central objective to develop a geographic unit that better captured the economic and social diversity of nonmetro areas in the United States (Tolbert and Sizer (1996)). In other literature, zip code areas have been used to investigate geographical disparities in health. For example, when investigating the maternal care deserts in Louisiana using zip code level data, Wallace et al. (2021), found that women living in parishes that lack access to maternal care suffer from an increase of 91% in their risk of death during pregnancy and up to one year postpartum. This paper however does not utilize commuting zones, or zip code areas, to distinguish areas but rather regions. The primary reason for this is due to the Cross-Wave Census Region/Division and Mobility File's compatibility with the RAND HRS Longitudinal File 2018 which provides access to a host of variables.

Table 1: Census Bureau-Designated Regions and Divisions

Region	Name	States
1	Northeast Region: New England Division	Maine, New Hampshire, Vermont, Massachusettes, Rhode Island, Connecticut
2	Northeast Region: Middle Atlantic Division	New York, New Jersey, Pennsylvania
3	Midwest Region: East North Central Division	Ohio, Indiana, Illinois, Michigan, Wisconsin
4	Midwest Region: West North Central Division	Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas
5	South Region: South Atlantic Division	Delaware, Maryland, District of Colombia, Virgina, West Virginia, North Carolina, South Carolina, Georgia, Florida
6	South Region: East South Central Division	Kentucky, Tennessee, Alabama, Mississippi
7	South Region: West South Central Division	Arkansas, Louisiana, Oklahoma, Texas
8	West Region: Mountain Division	Montana, Idaho, Wyoming, Colorado, New Mexico, Arizona, Utah, Nevada
9	West Region: Pacific Region	Washington, Oregon, California, Alaska, Hawaii

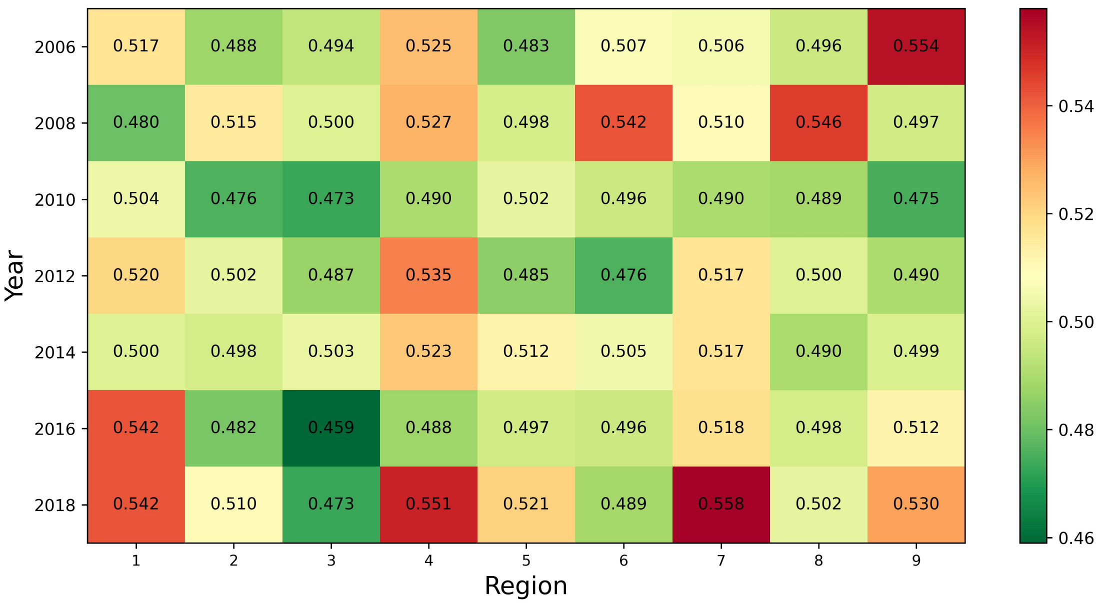
Note: This table outlines the nine regions, as per the Cross-Wave Census Region/Division and Mobility File, and the states included in the nine regions.

2.2 Theoretical Framework

Before we investigate the proposed research question, it is imperative that we define what is meant by a *"better (or worse) environment."* The research conducted by Russ-Eft (1979), made an early attempt to identify the different factors affecting neighborhood quality of life. However, neighborhood quality of life is a complex multi-dimensional concept which has meant that in the past there has been, and still is, disagreement within the literature regarding which indicators are most suitable to use as a metric of comparison when assessing neighborhood quality. Russ-Eft (1979) found that the different factors affecting neighborhood quality could be broadly categorized into five main groups. Specifically, environmental & physical conditions, economic conditions, facilities & services, political conditions, and lastly, personal characteristics & interpersonal relationships (Russ-Eft (1979)). Due to the multi-dimensional nature of neighborhood quality, previous research has utilized a variety of metrics and indicators: from air pollution levels to accessibility to public services such as education and hospital care.

This paper, however, chooses to make a distinction between neighborhoods based on their level of income inequality, which is sometimes also referred to as the level of economic heterogeneity within a neighborhood. Specifically, neighborhoods with a Gini coefficient closer to zero will be classified as better neighborhoods relative to those with a Gini coefficient closer to one. Furthermore, to ensure we are solely capturing the effects of local area income inequality, and not that of average income level, we will additionally control for the local average level of income. The motivation for using income inequality as a measure of neighborhood quality is supported by the findings of several papers which have all illustrated that individuals who reside in areas with a greater level of income inequality are more likely to suffer from health problems and higher mortality rates (Deaton (2003); Wilkinson and Pickett (2006)). Furthermore, the effects estimated from some of these studies are so strikingly large, that it reiterates the grave need for further research into the existing degree of geographic variation in health outcomes. For example, the findings of Lynch et al. (1998) suggested that the annual loss of lives that can be attributed to income inequality in the US is comparable to the loss of lives from lung cancer, diabetes, motor vehicle crashes, HIV, suicide, and homicide combined. To summarize, whilst this paper is indeed interested in unraveling the effects of one's local area on their health outcomes, it does so by using local area income inequality as a proxy for neighborhood quality.

Figure 1: Heat Map Summarizing the Gini Coefficients Across Regions per Year



Note: The above heat map summarizes the gini coefficients across the nine regions, denoted above in Table 1, per year. For details regarding how the gini coefficients are computed, the reader can see the sub-section 3.2, specifically 3.2.4 which addresses the classification of moves. Gini coefficients are color coded from red, illustrating higher gini coefficients and thus higher levels of income inequality, to green illustrating lower gini coefficients and levels of income inequality.

As previously mentioned, in this paper income inequality, is used as a proxy for neighborhood quality. Further, the gini coefficient is the metric which will be used to measure income inequality per region and enable regions to be ranked in relation to each other. Gini's were calculated per region, per year, which resulted in a total of 63 gini coefficients. The gini coefficients per region, per year, can be seen illustrated in the heat map Figure 1. As can be seen in the heat map, the gini coefficients do not vary too much and range from a minimum of 0.459 recorded in Region 3 in 2016 to a maximum of 0.558 in Region 7 in 2018. In addition to the gini's being calculated per region, per year, the average gini coefficient per region (across all years) is also calculated. The average region-level gini coefficient is used to rank the regions, in order of lowest to the highest level of income inequality. This ranking is then used to distinguish whether a move is classified as "good" or "bad." For example, individuals who move from Region 2 (which has an average gini coefficient of 0.496) to Region 4 (which has an average gini coefficient of 0.520) will be included in the "Bad move" sample, whilst those who move from Region 5 to Region 2 will be included in the "Good move" sample. Note, that because we take a region's average gini coefficient, across all years, the move from Region 2 to Region 4 will always be considered a bad move regardless of which year it takes place and this holds for all moves. In the Data section, the reader can find additional details regarding how the gini coefficients are computed. Including which formula is applied, as well as which variables and data sets are utilized.

3 Data

3.1 Data Sources

In order to answer the overarching research question, there are two key data sources required. Given that, simply put, this paper is interested in comprehending the effect of an individual's region of residence on their health outcomes over time, it is imperative that there is data on individual health outcomes. Specifically, this paper is interested in assessing the effects on Self-Reported Health, as well as three physical health measures, including BMI, Pulmonary Function, and Pulse. In addition to this, it is important to have data on an individual's region of residence, to distinguish how different regions affect individual health outcomes. Furthermore, given that this paper is interested in understanding how these relationships develop over time, it is important that the data is longitudinal in nature. Therefore, to summarise this thesis utilizes panel data, combining two data sets, to analyze how individuals' self-reported and physical health outcomes develop over time after moving regions and aim to uncover what temporal processes are at play. Namely, the two data sets are the RAND HRS Longitudinal File 2018 in combination with the Cross-Wave Census Region/Division and Mobility File.

The RAND HRS Longitudinal File consists of data obtained from the health and retirement study (HRS) core and exit interviews. Ultimately the health and retirement study is a longitudinal panel study that surveys a representative sample of roughly 20,000 individuals in America each year and obtains information regarding a large number of variables that cover everything from the demographics of respondents to their health and employment history. The RAND HRS file has a large array of variables including variables related to individuals' health and employment status. Including variables such as income, which will enable us to compute the gini coefficients for the nine regions, as well as the aforementioned individual health outcome variables.

The Cross-Wave Census Region/Division and Mobility File provides additional information regarding respondents' region of residence throughout the longitudinal survey. Specifically, it provides information regarding their region of residence in each survey year, their region of birth, their region of residence at age 10, and additional information regarding how far they moved after relocating. Fundamentally, the mobility file has data regarding which region individuals are living in, bi-annually, from the year 1992 to 2018. The data set categorizes the US into nine distinct regions, which can be summarised in Table 1 above. Importantly, this enables us to decipher where individuals were living throughout the duration of the study if they moved, and if so where they moved to and from.

3.2 Sample and Key Variables

3.2.1 Sample

The sample consists of individuals who have moved once, during the years 2006 to 2012. Although The RAND HRS Longitudinal File has information dating from 1992, only observations from 2006 to 2012 are considered in this study. The primary reason for this is that the enhanced face-to-face interviews were only introduced in 2006, and therefore there are no data points on physical health measures prior to this date. The Health and Retirement study, as previously mentioned, is a longitudinal panel study that surveys a representative sample of approximately 20,000 American citizens over the age of fifty. Therefore, the sample should adequately represent the American population over the age of fifty.

The reason for the chosen sample of interest is three-fold. It is well known that the US suffers from larger levels of health inequality than most economically developed countries, this is thought to be driven by substantial social gradients in the distribution of risk, protective and promoting factors which in turn manifest themselves as large social disparities in health outcomes (Halfon (2012)). Furthermore, the population of the United States, much like the population of many other countries in today's world, is aging. Some estimate that the population of Americans aged 65 years and older, will more than double by the year 2040, as compared to levels in 2010 (Odden et al. (2011)). Aging populations are a result of both the elevated birth rate during the "Baby Boom" of the mid 1900's, and an increase in life expectancy levels (Odden et al. (2011)). Moreover, Medicare, the federal health insurance program in place in the United States, which covers the medical costs of those aged sixty-five and higher. In 2019, it was estimated that sixty-three million Americans were covered under Medicare, coming in at just shy of a fifth of the American population at the time at 19% (Tarazi et al. (2022)). Therefore, the health outcome inequities present in the United States, coupled with their aging population and the structure of their federal health insurance program, Medicare, highlights the importance to understand the determinants of older individuals' health outcomes and to what degree they are affected by their region of residence.

3.2.2 Health Outcomes

Alongside, the primary variable of interest, *Self-Reported Health*, three additional physical measures will be investigated. As noted in the RAND HRS code book, from wave 8 (2006) onward, each wave, a sub-sample of HRS respondents are selected to complete what is referred to as an enhanced face-to-face interview. This enhanced face-to-face interview enabled data points to be collected on a range of bio-markers, three of which will be utilized in this thesis as physical health outcome measures. Namely, *BMI, Pulmonary function,* and *Pulse.* In the list below, the four health outcome variables are briefly defined.

1. *Self-Reported Health* reflects an individual's perception of their overall health, at any given time. Respondents are asked to rank their general level of health on a scale of (1) Excellent to (5) Poor. Where 2, 3, and 4 correspond to Very Good, Good, and Fair respectively. However, for simplicity this variable has been dichotomized such that (1) corresponds to a state of Good self-reported health, which captures levels 1, 2, and 3, and (0) corresponds to a state of Bad self-reported health, capturing levels 4 and 5.

2. *BMI* captures the respondent's Body Mass Index based on their measured height and weight, using the measurements recorded during the in-home physical measurements portion of the HRS interview, and is calculated by dividing their weight by their height squared ($BMI = \frac{Weight}{Height^2}$). As with BMI, all remaining physical measure variables summarise the respondent's measurements taken during the in-home measurements session.

3. *Pulmonary Function* is a measurement of the respondent's overall lung health and gives an indication of lung volume, capacity, rates of flow, and gas exchange. In order to obtain this measurement, a peak flow breathing test is administered and results are recorded in liters per minute. Higher readings indicate better overall lung health and a greater lung capacity.

4. *Pulse* is a commonly used health metric, it is a measure of an individual's heart rate and is measured in beats per minute.

3.2.3 Controls

In addition to the health outcome variables, there are two sets of control variables that will be used throughout the analysis to control for the effects of any differences in demographic and socio-economic characteristics. The first set of control variables consists of individual-level control variables and includes *Age* and *Income* for each individual at time t. In addition to the individual-level control variables, the second set of controls includes area-level control variables. Specifically, it includes *Average education, Average income* and *Employment*, for each region at time t. Note that because an individual fixed effects regression will be applied in the analysis, there is no need to control for time-invariant variables such as gender, race, or other individual characteristics that do not change over time.

3.2.4 Classification of Moves

Lastly, three variables were constructed in order to conduct this analysis. These variables include, *No. of Moves, Average Region Gini Coefficient* and *Move*. First *No. of Moves* is constructed to capture how many times the individuals moved region over the study period. This is computed by iterating over the Region of Residence in each wave of the survey and defining a move to occur when the Region of Residence in a wave t is different to that at wave t-1. The number of moves for individual i can therefore be formally defined as shown in equation one below.

$$Number\,of\,Moves_i = \sum_{t=1}^{T} I_{R_t \neq R_{t-1}}$$

Where I is an identity function such that:

$$I_{R_t \neq R_{t-1}} = \begin{cases} 1, & \text{if } R_t \neq R_{t-1} \\ 0, & \text{otherwise} \end{cases}$$

Next, the *Gini coefficient* was computed per region, per survey wave. This resulted in a total of sixty-three gini coefficients being computed. However, in order to simplify the empirical approach only the average region gini coefficient is considered. Hence an average of all gini coefficients captured for each region, across all survey years, is utilized in the analysis. It is formally defined below in equation two. The gini coefficient captures the level of income inequality, in each region, by iterating over the array of incomes x and computing the absolute difference between all possible pairs. It is then standardized, on a scale of 0-1, by dividing by the total number of potential pairs $2n^2$, multiplied by the average level of income in that region, $\bar{x}$.

$$Gini = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2n^2 \bar{x}}$$

Finally, *Move* was constructed which is a function that captures whether an individual's move is considered to be a "Bad move" or a "Good move." This variable is constructed by comparing the average gini coefficient of their new region of residence, to that of their old region of residence. Dependent on if the gini of the new region is higher, or lower than that of the old region the move will be classified as bad, or good respectively. Favoring regions that have lower levels of income inequality, and therefore gini coefficients closer to 0.

$$Move_i = \begin{cases} Bad, & \text{if } Gini_{New} > Gini_{Old} \\ Good, & \text{otherwise} \end{cases}$$

3.2.5 Mechanisms

Note, that the Results section is followed by the Mechanisms section. The Mechanisms section attempts to uncover if the changes in health outcomes subsequent to individuals moving region, can be explained by changes in behavioral habits triggered around the time of the move. The Mechanism section aims to provide some additional depth to the analysis and share insights regarding potential drivers of the changes in health outcomes, both physical and self-reported. This paper chooses three variables that broadly capture behavioral changes, which could be triggered by moving to a better, or worse area, and are known to have an effect on individual health. It includes *Smoking status, No. of days / week alcohol is consumed* and *Frequency of light exercise.* Where *Smoking status*, is a binary variable, which captures if, at the time of the interview, the respondent was a smoker (0) "No" or (1) "Yes". *No. of days / week alcohol is consumed* simply captures, according to the respondent, on average how many days per week they consume alcohol therefore it is a discrete numerical variable that ranges from 0, the respondent does not drink, to 7, the respondent drinks alcohol every day of the week. Lastly, *Frequency of light exercise* is an example of an ordinal categorical variable where the respondent's exercise habits are captured, outlining how frequently they partake in light exercise. These variables were taken directly from the RAND HRS Longitudinal File.

3.3 Summary Statistics

The summary statistics are presented in two sections, first, we distinguish individuals that undergo a good move, compared to those that undergo a bad move. This is important in order to get an indication of whether individuals who make a good move are systematically different from those who make a bad move. If there are underlying differences between the two groups of individuals, it becomes harder to verify whether the changes in health outcomes, subsequent to the move, are an effect of exposure to a region with lower, or higher, levels of income inequality. Second, we distinguish individuals based on the number of moves that they make; namely, individuals that have never moved, moved once, or moved multiple times. This is important because whilst studying movers enables a unique opportunity to study the effects of regions on individual health, this paper aims to understand how these findings can be more broadly applied to the wider population. Therefore, this comparison aims to clarify that movers do not have different underlying characteristics when compared to those who do not move, providing support for the external validity of this study. The two variables, $Move$ and $Number\,of\,Moves$, which are used to construct the sub-samples on which the summary statistics are computed are summarised formally below. Note, that in this section only the tables for the summary statistics across good and bad movers are included, should the reader be interested in the tables summarising the key variables across $Number\,of\,Moves$ they can be found in the appendix.

$$Move\,(M) = \{Bad,\, Good\}$$

$$Number\,of\,Moves\,(N) = \{0,\, 1,\, > 1\}$$

As can be seen in Table 2 below, there are close to no differences in average-level health variables across good and bad movers. Overall, the mean variable levels are very similar, particularly across Pulse, Pulmonary Function, and Self-Reported Health where the differences are minimal or in the case of Self-Reported Health non-existent. There is however a difference in the mean level of BMI worth noting, whilst individuals who made a good move have an average BMI of 27.65 those who made a bad move have an average BMI slightly higher, by 0.65 units, at 28.30. In addition to this Table 8, in the appendix, shows a similar story when looking at summary statistics across the Number of Moves. There are two minor differences here, which are worth highlighting. The first being, that those who do not move during the study seem to report themselves as marginally healthier, with a mean Self-Reported Health of 3.00, compared to those who have moved once and more than once which report a Self-Reported Health of 2.91 and 2.87, respectively. Whilst this difference appears to stand out in the summary statistics, it is important to mention that on a five-point scale, these differences relate to percentage differences of around 2.6% and 1.8% respectively. The second difference is that those who have moved more than once during the duration of the study, appear to have better Pulmonary

Functioning at 378 liters per minute compared to those who have not moved and have moved once at 365 and 367. This difference is likely due to the small sample size of individuals who have moved more than once which is considerably smaller at only 241 individuals. Overall, there appears to be no differences in baseline summary statistics between those who made a good, or bad, move or likewise between those who did not move, moved once, or more than once.

Table 2: Summary Statistics Health Outcomes and Control Variables

M = {*Bad, Good*}	Bad move				Good Move			
	Mean	Median	Std. Dev	No. obs	Mean	Median	Std. Dev	No. obs
BMI physical measure	28.30	27.65	5.57	339	27.65	26.59	5.57	306
Pulse	70.24	69	11.04	297	70.19	69.43	9.74	274
Pulmonary function	371.24	350	131.63	293	369.93	358.75	135.75	270
Self-reported health	2.90	2.86	0.93	339	2.90	2.8	0.96	307
Income	17504.10	17500	38256.88	339	18976.21	571.43	45381.05	307
Age	67.82	65.80	12.10	344	68.21	65.51	12.88	314

Note: This table summarises the descriptive statistics for key variables utilized in models 1, 2, 3, and 4, including health measures both self-reported and physical as well as age and income which are included as controls, over samples of individuals who made both good and bad moves.

Table 3: Summary Statistics Behavioural Variables

M = {*Bad, Good*}		Bad move			Good Move		
		%	Cum. %	Count	%	Cum. %	Count
Frequency of light exercise	(1) Everyday	6	1.8	6	3.6	3.6	11
	(2) >1 time / week	171	52.2	171	45.0	48.5	138
	(3) 1 time / week	104	82.9	104	28.7	77.2	88
	(4) 1 - 3 times / month	49	97.3	49	18.6	95.8	57
	(5) Never	9	100.0	9	4.2	100.0	13
Smoking status	(0) No	85.4	85.4	287	83.9	83.9	255
	(1) Yes	14.6	100.0	49	16.1	100.0	49
No. of days / week alcohol is comsumed	(0) Never	54.0	54.0	183	51.8	51.8	159
	(1) 1 day / week	16.8	70.8	57	16.9	68.7	52
	(2) 2 days / week	9.4	80.2	32	9.8	78.5	30
	(3) 3 days / week	6.2	86.4	21	6.5	85.0	20
	(4) 4 days / week	4.7	91.2	16	4.6	89.6	14
	(5) 5 days / week	3.8	95.0	13	3.3	92.8	10
	(6) 6 days / week	2.4	97.3	8	3.3	96.1	10
	(7) 7 days / week	2.7	100.0	9	3.9	100.0	12

Note: This table summarises the descriptive statistics for behavioral variables utilized in models 5 - 10, which are addressed in the Mechanisms section of the paper, over samples of individuals who made both good and bad moves.

4 Empirical Strategy

As mentioned in the introduction, this paper is interested in determining to what extent we see beneficial (or negative) effects of moving to a better (or worse region) on Self-Reported Health. The analytical approach is partly inspired by Alcock et al. (2014) which, exploits longitudinal data, to apply fixed effects regression to uncover temporal patterns of mental health after moving to an area with less (or more) green space. Given that there is a significant body of literature that suggests that mental health and self-reported health are strongly related, and often move together, this paper is primarily interested in determining if the temporal patterns illustrated by mental health levels, after moving to an area with more green space, are similar to those illustrated by self-reported health after moving to areas with decreased levels of income-inequality (an alternative proxy for neighborhood quality). However, this paper goes a few steps further and links self-reported health to a set of physical health measures, this is done to determine to what degree the improvements (or decreases) in self-reported health are reflected in physical health outcome measures indicating if they are indicative of true changes in individual health levels, or if perhaps moving region results in some placebo effect. The final step of the analysis entails determining what portion of the increases and decreases in physical health measures, can be explained by behavioral changes triggered by the move. This final step aims to develop a comprehensive understanding of the underlying mechanisms, or drivers, of changes in health outcomes subsequent to a move. Thus, this will be addressed in the mechanisms section. Therefore, the methodology will be addressed in two parts (1) Does Exposure to a Better (or Worse) Environment Result in Improvements (or Deterioration) of Individual Self-Reported Health? (2) Are Improvements in Self-Reported Health Indicative of Trends in Physical Health Measures? Should the reader be interested in the underlying mechanisms driving these changes in outcomes, the third and final question (3) To What Extent Can the Subsequent Improvements (or Decreases) in Physical Health Measures be Explained by Behavioral Changes Triggered by a Good (or Bad) Move? will be addressed in the Mechanisms section.

4.1 Assumptions

As stated above, this paper applies fixed effects regression analysis in order to address the research questions presented. In order to be able to draw causal interpretations from the findings, it is imperative that the causal assumptions of the model are fulfilled. The fixed effects regression model requires all of the typical multilinear regression assumptions to be fulfilled, and in addition to this, it requires its own, unique, strict exogeneity assumption to be fulfilled. Ultimately there are six multilinear regression assumptions that must be fulfilled to draw causal interpretations, this includes the causality, linearity, independence, normality, homoscedasticity, and the no multicollinearity assumption. A brief explanation of the aforementioned assumptions in the next paragraph.

The causality assumption entails that there must be a clear, logical line of reasoning or theoretical justification that suggests there is a causal relationship between an individual undergoing a good, or a bad, move and their health outcomes. In addition to this, the linearity assumption requires that the relationship between a good, or a bad, move and individuals' health outcomes is linear. The independence assumption demands that all observations must be independent of each other, meaning that the health outcomes for one individual should not be in any way related to the health outcomes of another individual. Furthermore, the normality assumption requires that the distribution of the dependent variable, health outcome, is normally distributed. In order for the homoscedasticity assumption to be fulfilled, the spread of the residuals should be constant across all levels of good and bad moves. Last, the multicollinearity assumption entails that the independent variables should not be highly correlated with each other. As mentioned earlier, the assumption which is central to the fixed effects regression model is the strict exogeneity assumption. This means that the estimates yielded from a fixed effects regression, will be unbiased if and only if the idiosyncratic shock (ε_{it}) is uncorrelated with the dependent variable, *Year Relative to Move*, in any point of time.

Unfortunately, not all seven assumptions can be statistically tested. Specifically, the causality assumption and the strict exogeneity assumption cannot be statistically tested, whilst the other five can. Therefore, the assumptions that can be tested will be, and the results will be discussed, whilst a discussion-based assessment will be provided for the remaining two assumptions. The Shapiro-Wilk, Breusch-Pagan, Variance Inflation Factor (VIF), Ramsey RESET, and Durbin-Watson statistical tests will be conducted in order to assess whether the normality, homoscedasticity, no multicollinearity, linearity, and independence assumptions are fulfilled respectively.

All of the aforementioned statistical tests are run on the fixed-effects regressions which are conducted in the results section below, with the same sample used to compute the results. Therefore all tests are run eight times, twice for each of the four models, across both good and bad movers. The test statistics and significance levels can be found in Tables 10, 11, 12, 13, and 14 in the appendix. The test statistics show that in most cases, the assumptions are fulfilled with an exception for the Shapiro-Wilk test. In fact, the significance levels for the Shapiro-Wilk tests for all models 1 through 4, across both good and bad movers, are below the significance level of 0.05, suggesting that the data is in-fact not normally distributed. The Breusch-Pagan test results show that most models, bar model 4 across bad movers, satisfy the homoscedasticity assumption. Similarly, the Ramsey RESET test result shows that most models satisfy linearity and that there is only evidence that the model suffers from misspecification for model 1 across bad movers and model 4 across good movers. Finally, the no multicollinearity and independence assumptions are satisfied in all cases. This can be seen in the test results as all Durbin-Watson test statistics are in the range of 1.069 - 1.703, where a test statistic of 2 indicates no autocorrelation and any test statistic below 1 indicates a cause for concern. Furthermore, all Variance Inflation Factors fall within the range of 1.085 - 1.46, where a common rule of thumb is if any Variance Inflation Factors are larger than a threshold of 5 this could be an indication that multicollinearity is high, this suggests there is no reason to consider multicollinearity to be an issue within the models presented.

Next, the strict exogeneity assumption will be addressed, fulfilling this assumption is key to being able to make causal claims through the application of a fixed effects model. As mentioned beforehand, the strict exogeneity assumption requires that the error term (ε_{it}) is uncorrelated with *Year Relative* *to Move* after controlling for the individual fixed effects (α_i). What this entails is that any changes in our outcome variables, for example, *Self-Reported Health* in model one, are attributed to only changes in *Year Relative to Move* and not at all to any unobservable time-invariant individual characteristics captured by ε_{it}, that may affect *Year Relative to Move* and *Self-Reported Health.* This assumption can be formally denoted, as such:

$$E(\varepsilon_{it}|year_{it}, \alpha_i) = 0$$

Through the use of panel data and the application of fixed-effects regression analysis, this results in the time-invariant unobservable characteristics of individuals being controlled for. Thus, addressing the endogeneity concern, assuming that any unobservable time-invariant characteristics that could affect Self-Reported Health and the choice to move are constant over time and thus captured by the individual fixed-effects term. This is thought to be likely, as the sample consists of individuals with an average age of around sixty-eight years old. Thus, it is reasonable to assume that those moving are most likely moving to a region in which they would like to retire, which is most likely their home region or a region in which they have strong social ties and a reliable support system. Therefore, it is considered reasonable to assume that the choice to move is not due to time-variant factors, but rather due to time-invariant characteristics that the individual possesses.

4.2 Model Specification

4.2.1 Does Exposure to a Better (or Worse) Environment Result in Improvements (or Deterioration) of Individual Self-Reported Health?

Concretely, this question is interested in determining if self-reported health exhibits the same temporal patterns, as mental health, in the time leading up to and following the move to a region that is more or less desirable. In order to address this first part of the analysis, a fixed-effects regression is conducted as is done in Alcock et al. (2014) [3] As a result of the longitudinal nature of the data, it is possible to estimate the effects of time relative to the move, capturing years of exposure to new regions but also exposure to old regions in the lead-up to the move, as well as controlling for additional control variables. Through including a set of control variables, the variation due to changing circumstances such as age, income, and employment are controlled for. Further, as a result of estimating a fixed-effects estimator all time-invariant factors[4] which may affect our outcome variables are controlled for and captured in the individual fixed-effect term. The basic model can be denoted as such:

$$SRH_{it} = \alpha_i + \beta\, year_{it} +_y X_{it} +_y Z_{it} + \varepsilon_{it} \tag{1}$$

Where X and Z are sets of individual level, and area level, control variables:

$${}_yX_{it} = \gamma\, age_{it} + \delta\, income_{it}$$

[3]Whilst Alcock et al. (2014) classifies greener areas as more desirable, this paper classifies areas with lower gini coefficients as more desirable. In the paper published by Alcock et al. (2014), there was evidence to support the shifting-baseline hypothesis when individuals undertook a good move, this was illustrated by improved levels of mental health within a year of the move which was then maintained at approximately the same rate for the following two years. The evidence illustrated by Alcock et al. (2014) for those who undertook a bad move, was less clear however.

[4]This could include time-invariant factors such as individuals' genetics, an individual's genetic makeup can directly influence an individual's susceptibility to developing certain diseases and health conditions.

$${}_y Z_{it} = \lambda\, average\, education_{it} + \kappa\, average\, income_{it} + \rho\, employment_{it}$$

Where SRH_{it} is a binary variable that captures a measurement of individual i's self-reported health, at time t, where (1) corresponds to "Good" self-reported health and (0) corresponds to "Bad" self-reported health. The α_i, is the unobserved individual level component, which is the key characteristic of a fixed-effect model as it decomposes the error term into an individual fixed-effect component (α_i) which absorbs all time constant unobserved factors affecting SRH and an idiosyncratic error (ε_{it}) which captures the remaining variation specific to the individual and time period. Next, $year_{it}$ summarises the year relative to the move for individual i at time t, such that β captures the anticipation effects prior to the move and the exposure effects post move. Last, two sets of control variables are included in the regression set X which includes individual-level controls specifically age and income, and set Z which includes region-level controls including employment rate, average income, and average years of education.

These results, plot on a line graph will help visualize how *Self-reported Health* moves in the years before, and after, an individual moves region.

Note, that whilst similar studies often take the period prior to moving as the reference period, this paper chooses to take two periods prior to moving as the reference period (T-2). The primary reason for this is, that it is interesting to see if the anticipation of moving to a better (or worse) area has any effects on an individual's Self-Reported Health, or behavioral habits. This once again is partly inspired by the empirical approach presented in Alcock et al. (2014), which investigated similar effects of the anticipation of moving to a greener (or less green) area on mental health.

4.2.2 Are Improvements in Self-Reported Health Indicative of Trends in Physical Health Measures?

Next, to address the second part of the analysis three more fixed-effect regressions will be run, but this time on physical health measures. These regressions will be identical to the model introduced in the first part of the analysis (regression (1)), however, the outcome variable will be replaced with one of three of the physical health measures studied within this paper. Models 2, 3, and 4 are denoted below, which aim to explain the effects of time-relative to the move on *BMI*, *Pulmonary Function*, and *Pulse* respectively.

$$BMI_{it} = \alpha_i + \beta\, year_{it} +_y X_{it} +_y Z_{it} + \varepsilon_{it} \tag{2}$$

$$Pulmonary function_{it} = \alpha_i + \beta\, year_{it} +_y X_{it} +_y Z_{it} + \varepsilon_{it} \tag{3}$$

$$Pulse_{it} = \alpha_i + \beta\, year_{it} +_y X_{it} +_y Z_{it} + \varepsilon_{it} \tag{4}$$

The results will once again be illustrated both in a table and plotted on a line graph. This will once again help visualize how physical health measures move around the move, and if changes in individuals' Self-reported Health are indeed indicative of changes in individuals' physical health measures. These results, together with the results from the first model, will clarify if changes in self-reported health levels are supported by changes in physical health measures and if so if the same temporal patterns can be seen in both self-reported health and physical measures.

Before discussing the results it is imperative to highlight that each fixed-effects model, models 1 to 4, was run two times. Once on a sub-sample of individuals who made what has been classified as a "Bad move," and then again on a sub-sample who made what has been classified as a "Good move."

5 Results

The results collated from the analysis will be addressed in the same order in which the models were introduced in the methodology.

5.1 Does Exposure to a Better (or Worse) Environment Result in Improvements (or Deterioration) of Individual Self-Reported Health?

In order to tackle the central research question, our primary focus is on first tackling sub-question 1.1, thus, we focus on model 1. This section of the analysis focuses on understanding if individuals experience gains in self-reported health prior to moving to areas with lower levels of income inequality, and if the opposite is seen when individuals relocate to areas with higher levels of income inequality.

The results obtained from model one show that movers who embarked on a "Bad move," and moved to regions with higher levels of income inequality, relative to their old regions, saw no statistically significant differences in self-reported health levels, at T-1, T+1, or T+2 relative to T-2. However, whilst movers who moved to regions with lower levels of income inequality, classified as a "Good move," also saw no statistically significant difference in self-reported health levels at T-1 relative to T-2, they did see statistically significant improvements in T+1 and T+2. These slight improvements in self-reported health measures are represented by the coefficients, shown in Table 4, 0.0956 and 0.0720 which are statistically significant at the 5% and 10% significance levels respectively. Given that self-reported health has been dichotomized, such that 1 captures Good Self-Reported Health and 0 captures Bad Self-Reported Health, these coefficients capture the increase (or decrease) in the likelihood that individuals, belonging to either the good move or bad move cohorts, deem themselves as having good health. Thus, the coefficient of 0.0956 can be interpreted as such, conditional on undergoing a good move, individuals are on average approximately 9.6% more likely to state their Self-Reported Health as Good (Excellent, Very Good, or Good), rather than Bad (Fair, Poor), one period postmove. Similarly, they are approximately 7.2% more likely to state their Self-Reported Health as good two periods postmove.

Note, that whilst the remaining coefficients were not statistically significant, they were all positive in their sign across both good and bad moves, this is clearly illustrated in Figure 2.1 below. Therefore, would they have been statistically significant, they would have been interpreted as improvements in Self-Reported Health levels. Whilst there is no statistical evidence to suggest that those who moved to areas of higher income inequality experienced increases in their Self-Reported Health there are reasons why this could be justified. For example, it could be that, due to the mean sample age, a substantial amount of these individuals are moving back to their home states as a result of recent retirement. Furthermore, moving back home could in turn mean being closer to family, and friends. Alongside this, it is becoming increasingly more known that loneliness, particularly amongst the elderly, is a common source of suffering and impaired quality of life (Perissinotto et al. (2012)). In fact, Perissinotto et al. (2012) found that loneliness was even significantly associated with an increased risk of death, for elderly people, within a six-year follow-up period when controlling for demographics, socio-economic status as well as depression, and other health controls. Therefore, whilst individuals may have relocated to an area with higher levels of income inequality perhaps the negative effects of this are offset by their close social circle, and support system of their new region.

Table 4: The effect of period relative to move on self-reported health

Period Relative to move	Bad move (1)	Good move (2)
1 period premove (T-1)	0.0120	0.0395
	(0.0373)	(0.0395)
1 period postmove (T+1)	0.0324	0.0956**
	(0.0388)	(0.0406)
2 periods postmove (T+2)	0.0315	0.0720*
	(0.0415)	(0.0429)
No. of obs	344	314

Note: This table reports estimates of anticipation and exposure effects on individuals' self-reported health levels for two different subgroups, the results summarised in this table are captured by Model 1. Column (1) reports the estimates for those individuals who moved to a region with a higher level of income inequality, relative to their original region of residence which consists of a sample size of 344 individuals. Column (2) reports the estimates for those who moved to a region with a lower level of income inequality which consists of a sample size of 314 individuals. All anticipation and exposure effects are calculated relative to two periods before the move (T-2), which is four calendar years prior to the move as each survey wave consists of two years. Heteroskedasticity and autocorrelation consistent (HAC) standard errors are reported in brackets whereas the p-value is expressed as: $(***)$ $p < 0.01$; $(**)$ $p < 0.05$; $(*)$ $p < 0.10$.

The results presented above, are in line with the result illustrated by Fiscella and Franks (2000) which found that income inequality did appear to have small effects on Self-Reported Health. Although, the findings presented in Shi and Starfield (2000) found much more substantial effects of income inequality on Self-Reported Health. In fact, Shi and Starfield (2000) reported that individuals living in areas with lower levels of income inequality were anywhere between 1.2 to 1.3 times more likely to report themselves as having good self-reported health than their counterparts living in areas with higher levels of income inequality. These effects are considerably more sizeable than those reported in this paper, however, it is likely that this is due to differences in the length of exposure between the studies.

Note, that whilst the explanatory Year Relative to Move variables (T-1, T+1, and T+2) in Model 1 when performed on the good move sub-sample, were jointly statistically significant at the 5% level, they were not jointly significant when performed on the bad move sub-sample. The reader can find the results from the Wald Test of joint significance, in Table 16, included in the appendix.

5.2 Are Improvements in Self-Reported Health Indicative of Trends in Physical Health Measures?

In order to tackle the next sub-question, question 1.2, we turn our attention to the physical health measures and models 2, 3, and 4. The intention of this next part of the analysis was to uncover whether the changes that we see in Self-Reported Health subsequent to a good (or bad) move are truly indicative of changes in physical health measures. For example, if after moving to a region with lower levels of income-inequality individuals reported better self-reported health outcomes across the board – would this also be evident in better physical measures, and if so, do the physical health measures display the same temporal patterns to reach these higher average levels?

Before delving into the results of the physical measures, it is important to point out that across all three physical measures, BMI, Pulmonary Function, and Pulse, there are no statistically significant coefficients indicating an effect of year relative to move.

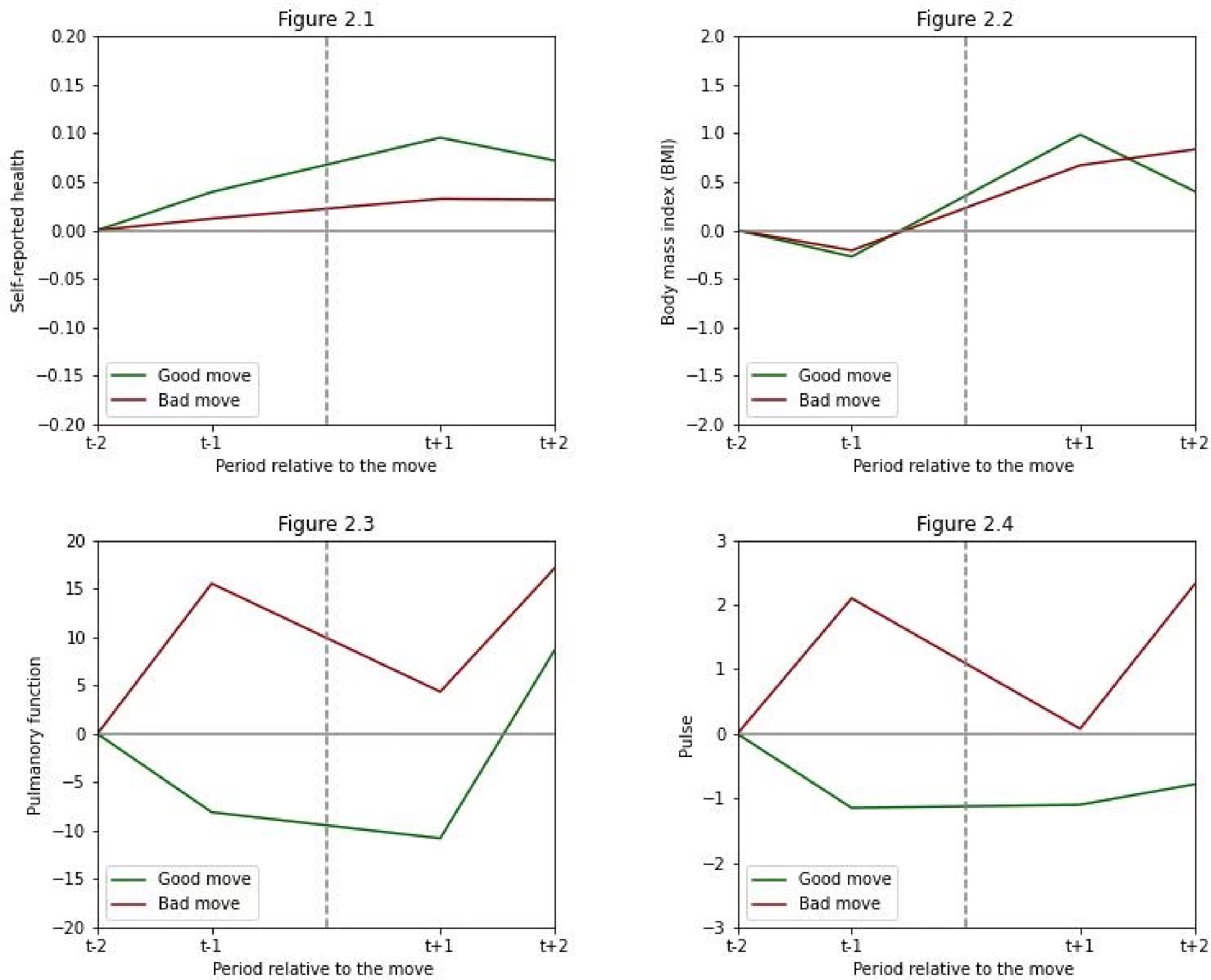
Looking first at the results from model 2, it can be seen that, although the coefficients are not statistically significant, the time relative to move patterns are similar across both the bad and good move sub-samples. In T-1, there is a decrease in BMI's which is then followed by an increase in BMIs in T+1 for both good and bad moves. After which, those in the bad move sub-sample once again experience an increase in average BMI levels in T+2, larger than that experienced in T+1, suggesting that BMI levels could still be increasing. Those in the good move sub-sample also once again experience an increase in average BMI levels in T+2 however, unlike those in the bad move sub-sample, this increase is smaller than the increase experienced in T+1 suggesting that BMI levels could be reverting back to pre-move levels, or lower. However, whilst there is no statistically sound evidence, this could provide a reason to believe that in the initial years after moving individuals experience similar changes to their physical measures regardless of their new region of residence.

Model 4 illustrates how pulmonary function moves around the time of a move in region, once again, much like with model 2, there are no statistically significant coefficients captured on either the good, or bad move regression. Interestingly, when looking at a bad move, individuals actually experienced increased pulmonary function in periods T-1, T+1, and T+2 relative to T-2. Not only do all coefficients suggest increased pulmonary function, but the largest coefficient, 17.094, in fact, is recorded in T+2, the period in which the individual has spent the longest amount of time in their new region surrounded by higher levels of income inequality. This pattern of increasing levels of pulmonary function, taking place after a bad move, although not supported by statistically significant evidence, is not in line with what was anticipated. However, when looking at the results captured in the good move regression although once again, they are not supported by statistically significant coefficients, they do exhibit what can be expected after a move to a more favorable region. Namely, although decreases in pulmonary function are recorded in both periods T-1 and T+1, this is followed by a sizeable increase, of 8.6231 liters per minute, in T+2. Suggesting, that whilst it may take time for the effects of a good move to positively influence one's health that it could still be a feasible assumption to make.

Similarly, when investigating how pulse moves before, and after, both good and bad moves model 3 also fails to capture any statistically significant coefficients. However, saying that unlike with BMI the patterns in time relative to move Pulse predictions are not similar across good, and bad moves, in fact, the predicted coefficients move in opposite directions. Looking at the results for the bad move sub-sample, it can be seen that initially there is an increase in pulse predictions at T-1 relative to T-2, which is followed by a very marginal increase bringing it almost back to T-2 levels in T+1, which is once again followed by an increase similar to that experienced in T-1 in T+2. Whilst those in the good move sub-sample, have steadily decreasing predicted pulse coefficients, experiencing the largest decrease in T-1, and subsequently smaller decreases in each period. Suggesting, that perhaps a good move results in initially lowered pulse levels but these revert back to levels similar to those experienced in T-2. It must also be mentioned that across both sub-samples, the largest coefficient in magnitude was 2.32, which is a relatively minor change in pulse.

Overall, the results captured across physical health measures do not paint a very clear picture. To summarise, time relative to a good move appeared to be associated with increased levels of BMI, initially decreased levels of Pulmonary Function followed by increases in the final year of measurement, and decreased levels of Pulse. Whilst time relative to a bad move appeared to be associated with similarly increased levels of BMI, increased levels of Pulmonary Function, and increased levels of Pulse. The statistically significant improvements in Self-Reported Health, across good movers, in periods T+1 and T+2 are therefore supported to some degree by associations in increased Pulmonary Function in T+2 and decreased levels in Pulse in both T+1 and T+2. Note, that the explanatory Year Relative to Move variables (T-1, T+1, and T+2) in Models 2, 3, and 4, when performed across both good and bad move sub-samples, were not jointly statistically significant. The reader can find the results from the Wald Test of joint significance, in Table 16, included in the appendix.

Figure 2: The Effect of Year Relative to Move on Self-Reported Health, BMI, Pulmonary Function, and Pulse



Note: This figure provides a visualization for the results captured in Tables 4 and 5 above. Figure 2.1 plots the coefficients of the estimated exposure effects on individuals' Self-Reported Health levels produced by Model 1, on an event study graph. Similarly, Figure 2.2 illustrates the coefficients of the estimated exposure effects on BMI captured by Model 2, Figure 2.3 illustrates the coefficients of the estimated exposure effects on Pulmonary Function captured by Model 3, and Figure 2.4 illustrates the coefficients of the estimated exposure effects on Pulse captured by Model 4. Note that in each of the four sub-figures, the estimated coefficients for both good move and bad move are illustrated, distinguished by colored lines.

Table 5: The effect of period relative to move on individual's physical health measures: BMI, Pumlanory function and Pulse

	BMI		Pulmonary Function		Pulse	
	Bad move	Good move	Bad move	Good move	Bad move	Good move
	(1)	(2)	(3)	(4)	(5)	(6)
1 period premove (T-1)	-0.2078	-0.2719	15.516	-8.0954	2.1002	-1.1476
	(0.8017)	(0.8528)	(16.285)	(17.704)	(1.5759)	(1.5897)
1 period postmove (T+1)	0.6714	0.9882	4.3461	-10.798	0.0778	-1.0985
	(0.8671)	(0.8381)	(17.534)	(17.394)	(1.5759)	(1.5641)
2 period postmove (T+2)	0.8344	0.4031	17.094	8.6231	2.3151	-0.7816
	(0.9066)	(0.9354)	(18.073)	(19.445)	(1.7575)	(1.7607)
No. of obs	344	314	344	314	344	314

Note: This table reports estimates of anticipation and exposure effects on individuals' physical health measures levels for two different subgroups. The results summarised in this table are captured by Models 2, 3, and 4. Columns (1, 3, and 5) report the estimates for individuals who moved to a region with a higher level of income inequality, relative to their original region of residence; consisting of a sample size of 344 individuals. Columns (2, 4, and 6) report the estimates for those who moved to a region with a lower level of income inequality; consisting of a sample size of 314 individuals. Furthermore, the anticipation and exposure effects are investigated on three different physical health measures. Columns (1) and (2) investigate the effects on BMI, Columns (3) and (4) focus on Pulmonary Function, and Columns (5) and (6) look at Pulse. All anticipation and exposure effects are calculated relative to two periods before the move (T-2), which is four calendar years prior to the move as each survey wave consists of two years. Heteroskedasticity and autocorrelation consistent (HAC) standard errors are reported in brackets whereas the p-value is expressed as: $(***)$ $p < 0.01$; $(**)$ $p < 0.05$; $(*)$ $p < 0.10$.

6 Mechanisms

To finalize the analysis, three potential drivers for health outcomes are investigated. To determine whether the changes in health outcomes, identified after moving, can be explained by behavioral changes triggered by the move.

There is a vast body of literature that suggests that our daily behaviors, dependent on how healthy (or unhealthy) they may be, can have substantial effects on our health outcomes. Although, the potential health gains from achievable behavioral changes are often brushed off by individuals, and thought to be minor. Yet, evidence from a recent paper suggests that adherence to a Mediterranean diet and a healthy lifestyle, which considered things such as alcohol consumption, smoking, and physical activity, has been associated with all-cause and cause-specific mortality rates of more than 50% lower in elderly individuals aged between 70 to 90 years old (Knoops et al. (2004)). Therefore, this thesis chooses to hone in on three key behavioral mechanisms, including Drinking measured as the frequency of alcohol consumption, Exercise measured as the frequency of light exercise and Smoking which is measured as the individual's current smoking status.

Alcohol consumption has been perhaps one of the most widely debated unhealthy behaviors, whilst it is widely accepted that excessive alcohol consumption is bad for one's health some studies have found that light to moderate alcohol consumption could even yield beneficial health effects. For example, amongst women alcohol consumption was previously found to be associated with better self-reported health, improved rates of cardiovascular health, as well as lower rates of hospitalization (Balsa et al. (2008)). However, a more recent study conducted by Burton and Sheron (2018) clearly demonstrated that the effects of alcohol on both death and disability are substantial and larger than had been previously thought. This study also highlighted alcohol as the seventh leading risk factor in death amongst both men and women, accounting for 6.8% of deaths among men and 2.2% of deaths among women (Burton and Sheron (2018)). These findings led the Chief Medical Officer of the UK to remark that there is "no safe level of alcohol consumption," contradicting previous schools of thought which suggested that light alcohol consumption was harmless and potentially in some cases even beneficial for one's health (Burton and Sheron (2018)).

On the other hand, there is little debate about the benefits of physical activity. Physical activity, or light exercise, is known to have a whole host of benefits, particularly for elderly individuals. In fact, it has been known to soothe adverse side-effects of chronic diseases and prevent the decline of individuals' motor skills which is associated with early death and disability in older individuals (Carta et al. (2021)). In addition to this, physical activity also has positive effects on both an individual's overall quality of life and their biological rhythms (Carta et al. (2021)).

Similarly, there is nowadays little debate regarding the harms that accompany the habit of smoking. In fact, smoking cigarettes has been referred to as the single largest avoidable cause of death, and disability, across developed countries (of Health et al. (2014)). Smokers are significantly more likely than non-smokers to develop fatal respiratory cancers, chronic obstructive pulmonary disease, or suffer a cardiac arrest (of Health et al. (2014)). Yet, the cessation of smoking improves an individual's life expectancy at any age. For example, whilst lifelong smokers lose on average ten years from their life expectancy, if an individual stops smoking at the age of forty they can recover nine out of these ten years, should they only stop at sixty years old they can still recover four out of these ten years (West and Stapleton (2008)).

6.1 Model Extension and Further Analysis

Last, in order to answer the second research question, this paper will additionally focus on three behavioral variables specifically smoking, drinking, and exercise. To determine whether changes in self-reported health and physical health measures identified after moving can be to some degree explained by behavioral changes triggered by the move. To answer this question, two sets of regressions are conducted. The first includes three fixed-effects regressions (models 5, 6, and 7) similar to those discussed above, with the behavioral variables of interest as the dependent variables. This enables us to determine if individuals show signs of behavioral change, after moving to a better, or worse, region. For example, do individuals pick up healthy habits, such as increased frequency of exercise, after moving to a better region? Or, on the other hand, do we see an increase in alcohol dependency when individuals move to a less favorable region, with higher levels of income inequality? This enables us to visualize the patterns in individuals' behaviors and determine if there is reason to believe that certain behaviors were triggered by a good, or bad, move.

$$Drinking_{it} = \alpha_i + \beta\, year_{it} +_y X_{it} +_y Z_{it} + \varepsilon_{it} \tag{5}$$

$$Exercise_{it} = \alpha_i + \beta\, year_{it} +_y X_{it} +_y Z_{it} + \varepsilon_{it} \tag{6}$$

$$Smoking_{it} = \alpha_i + \beta\, year_{it} +_y X_{it} +_y Z_{it} + \varepsilon_{it} \tag{7}$$

Similarly to the approach taken with models 1 to 4, the fixed-effects models 5 to 7, are run twice. Once on a sub-sample of individuals who made what has been classified as a "Bad move," and then again on a sub-sample who made what has been classified as a "Good move."

In addition to the fixed-effects regression models denoted above there will also be a second set of regression models. Specifically, there will be a set of multivariate regression models run on each physical health measure analyzed within this paper, to see what portion of the variance in these physical measures can be captured and explained by the three behavioral measures chosen. The multivariate regression models will also include both the set of individual-level control variables and area-level control variables which were included in the fixed-effects regression models, and they can be seen denoted below as models 8, 9, and 10.

$$BMI_{it} = \beta_0 + \beta_1\, drinking_{it} + \beta_2\, exercising_{it} + \beta_3\, smoking_{it} +_y X_{it} +_y Z_{it} + \upsilon_{it} \tag{8}$$

$$Pulmonary\, Function_{it} = \beta_0 + \beta_1\, drinking_{it} + \beta_2\, exercising_{it} + \beta_3\, smoking_{it} +_y X_{it} +_y Z_{it} + \upsilon_{it} \tag{9}$$

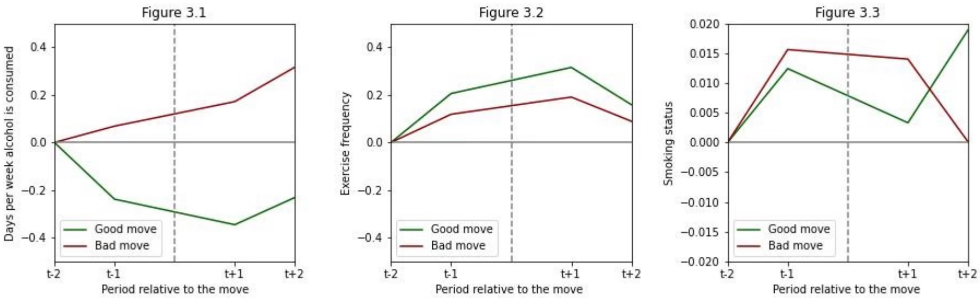
$$Pulse_{it} = \beta_0 + \beta_1\, drinking_{it} + \beta_2\, exercising_{it} + \beta_3\, smoking_{it} +_y X_{it} +_y Z_{it} + \upsilon_{it} \tag{10}$$

6.2 Supplementary Results

6.2.1 To What Extent Can the Subsequent Improvements (or Decreases) in Physical Health Measures be Explained by Behavioral Changes Triggered by a Good (or Bad) Move?

To answer the second research question, two sets of regressions are conducted. The first includes three fixed-effects regressions (models 5, 6, and 7) similar to those discussed above, with the behavioral variables of interest as dependent variables. The three behavioral variables of interest are Drinking, Exercise, and Smoking. Much like the fixed-effects regressions discussed above, models 1, 2, 3, and 4, most of the time relative to move coefficients are not statistically significant which once again limits the confidence with which conclusions can be drawn.

Figure 3: The Effect of Year Relative to Move on Alcohol Consumption, Exercise Frequency, and Smoking Status



Note: This figure provides a visualization for the results captured in Table 6 above. Figure 3.1 plots the coefficients of the estimated exposure effects on individuals' Alcohol Consumption levels produced by Model 5, on an event study graph. Similarly, Figure 3.2 illustrates the coefficients of the estimated exposure effects on Exercise Frequency captured by Model 6, and Figure 3.3 illustrates the coefficients of the estimated exposure effects on Smoking Status captured by Model 7. Note that in each of the four sub-figures, the estimated coefficients for both good move and bad move are illustrated, distinguished by colored lines.

When looking at model 5, which investigates the time relative to move effects on drinking, it can be seen that although there is only one statistically significant coefficient the patterns and signs of the coefficient are consistent with what is to be expected from a desirable and unfavorable move of region. Namely, one can see that from the results obtained from those who made a bad move, to an area with higher levels of income inequality the time-relative to move coefficients are increasing in nature. Specifically, it can be seen that T-1, T+1, and T+2 are 0.0684, 0.1714, and 0.3159, respectively. Suggesting that the longer one spends exposed to the region with higher income inequality the more their weekly alcohol consumption increases. In a similar manner, it can be seen for those who made a good move, to an area with lower levels of income inequality, individuals experience decreasing coefficients indicating decreasing levels of alcohol consumption. Although, if you take a closer look at the coefficients for T-1, T+1, and T+2 you will see that they are -0.2381, -0.3453, and -0.2311 respectively. So, although they are decreasing, given that the decrease in period T+2 is smaller than that of T+1 this could suggest that individuals are stabilizing at a new slightly lowered level of alcohol consumption, or that they are reverting back to old habits and their pre-move alcohol consumption levels. Further, it should be highlighted that the coefficient of T+1, for the good-move sub-sample, is indeed statistically significant at the 10% significance level. Suggesting that in T+1 there is statistically sound evidence to suggest, that those who made a good move, drink on average 0.3453 days less per week, which can be interpreted as drinking approximately 1 day less every three weeks. Whilst this may not sound like a substantial amount, it accumulates to approximately 17 days a year.

Model 6 illustrates the time-relative to move effects on individuals' frequency in which they partake in light exercise. Because the variable light-exercise is a categorical variable, in which individuals rank how frequently they partake in light exercise on a scale of 1 "Every day" to 5 "Never," and that the increases between integers do not correspond with linear increases in frequency it can make the interpretation of the coefficient's complicated. However, it can give us a general idea as to whether individuals increased, or decreased, their exercise regimes. Interestingly enough, the same decreasing pattern in exercise frequency can be seen across both sub-samples. For those in the bad move subsample, we see two periods of steadily decreasing rates followed by a smaller decrease in T+2. In addition to this, it should be mentioned that the coefficient of T+1 is statistically significant at the 5% level, suggesting that there is indeed evidence to support the notion that two years post moving to an area with higher levels of income inequality individuals participate in light exercise less frequently. The same pattern can be seen by those who made a good move, T-1 and T+1 show steadily increasing coefficients at 0.2055 and 0.3149, which is followed by a smaller increase of 0.1506 in T+2. In addition to this, both coefficients T-1 and T+1 are statistically significant, at the 5% level and the 1% level respectively. This suggests that there is evidence to support the notion that although decreasing exercise levels can be seen two years after moving to a region with lower levels of income inequality, they can also be seen in the two years before the move. A potential reason why we may have seen decreasing exercise levels in both sub-samples could be due to the demographic composition of the data set, which consists mainly of retirees. Although age was controlled for, there could be other factors such as the onset of mobility issues such as arthritis, which were not controlled for and have negative implications for an individual's ability to exercise.

To determine whether the effects of time relative to a good, or bad, move influence an individual to pick up or quit smoking we draw our attention to the results of model 7. Firstly, it is worth mentioning that none of the time relative to move coefficients, across both good and bad moves is statistically significant. In addition to this, all coefficients are positive suggesting that if time relative to a move does affect an individual's decision to smoke it is likely that it influences them to pick up smoking, as a positive coefficient shows an increased likelihood that an individual is, on average, a smoker. Although this being said, it is also imperative to highlight the magnitude of all of the time-relative to move coefficients, they all fall in the range of 0.0001 to 0.0189 which suggests an individual's likelihood to be a smoker increases anywhere between a negligible 0.01% and 1.89%. Suggesting, that a move to a good, or a bad area, is very unlikely to have any effect on an individual's decision to pick up, or quit, smoking.

Note, that whilst the explanatory Year Relative to Move variables (T-1, T+1, and T+2) in Model 6 were jointly statistically significant, when performed on both the good and bad move sub-samples at the 1% and 10% significance levels respectively, they were not jointly significant in Models 5 and 7 when performed on either the good or bad move sub-samples. The reader can find the results from the Wald Test of joint significance, in Table 16, included in the appendix.

In addition to the results obtained from the fixed-effects regressions, the second set of regressions uses multivariate regression analysis to determine what proportion of the variation in the physical health measures can be explained by the behavioral variables.

Model 8 describes how much of the variation in BMI can be explained by the behavioral variables of interest: drinking, exercising, and smoking in addition to our two sets of individual-level and area-

Table 6: The effect of period relative to move on individuals health behaviors: Drinking, Exercising and Smoking

	Drinking		Exercise		Smoking	
	Bad move	Good move	Bad move	Good move	Bad move	Good move
	(1)	(2)	(3)	(4)	(5)	(6)
1 period premove (T-1)	0.0684	-0.2381	0.1183	0.2055**	0.0156	0.0124
	(0.1729)	(0.1951)	(0.0905)	(0.1028)	(0.0294)	(0.0319)
1 period postmove (T+1)	0.1714	-0.3453*	0.1905**	0.3149***	0.0140	0.0033
	(0.1794)	(0.2004)	(0.0940)	(0.1056)	(0.0306)	(0.3270)
2 period postmove (T+2)	0.3159	-0.2311	0.0890	0.1586	0.0001	0.0189
	(0.1925)	(0.2117)	(0.1007)	(0.1115)	(0.0327)	(0.0345)
No. of obs	344	314	344	314	344	314

Note: This table reports estimates of exposure effects on individuals' behavioral habits for two different subgroups, the results summarised in this table are captured by Models 5, 6, and 7. Columns (1, 3, and 5) report the estimates for those individuals who moved to a region with a higher level of income inequality, relative to their original region of residence which consists of a sample size of 344 individuals, whilst Columns (2, 4, and 6) report the estimates for those who moved to a region with a lower level of income inequality which consists of a sample size of 314 individuals. Furthermore, the exposure effects are investigated on three different physical health measures, Columns (1) and (2) investigate the effects on Drinking, Columns (3) and (4) focus on Exercise, and Columns (5) and (6) look at Smoking. All exposure effects are calculated relative to two periods before the move (T-2), which is four calendar years prior to the move as each survey wave consists of two years. Heteroskedasticity and autocorrelation consistent (HAC) standard errors are reported in brackets whereas the p-value is expressed as: $(***)$ p <0.01; $(**)$ p <0.05; $(*)$ p <0.10.

level control variables. As can be seen from the results, both drinking and smoking have negative effects on an individual's BMI. Smoking specifically results in a decrease in BMI of approximately 2.74, and this effect appears to be statistically significant at the 1% level. This result is somewhat expected, as smoking is often regarded as an appetite suppressant which may be a reason why individuals who smoke see decreased BMI levels. However, drinking resulting in reduced BMI levels is somewhat surprising. The coefficient for drinking is 0.43 suggesting that with each additional day, an individual consumes alcohol, they experience a decrease in their BMI of 0.43, this coefficient is also statistically significant at a 1% level. Although this is surprising, there are lines of argumentation that could provide sound argumentation as to why this may be the case. If individuals only consume alcoholic beverages when socializing with friends, this could be an indication that they are living a more socially active lifestyle rather than engaging in less energy-intensive activities such as sitting at home watching television on the couch. Last, the coefficient of light exercise is approximately 0.62, given that exercise is measured on a scale of 1 every day to 5 never, this is consistent with the argument that increased exercise results in a decrease in an individual's BMI. This effect is also statistically significant at a 1% level.

To determine what effect our behavioral variables have on pulmonary function, model 9 can be consulted. The first result that seems alarmingly large is the smoking coefficient, according to the results if an individual is a smoker, they have on average a pulmonary function that is approximately 40 liters per minute lower than that compared to a non-smoker. This is not a surprising finding, given that smoking is known to have detrimental effects on an individual's lung health. It is also important to note that this coefficient is statistically significant at a 1% level of significance. In addition, the results illustrate that individuals who exercise less (thus have a higher rating on the exercise scale of 1 to 5) also exhibit lower levels of pulmonary function, this effect is also statistically significant at a 5% significance level. Last, it can be seen that with increased drinking an individual supposedly exhibits increased pulmonary function, in fact for every additional day during a week on which an individual consumes alcohol they exhibit on average an increase of approximately 5 liters per minute in their pulmonary function levels. This coefficient is also statistically significant at a 5% level. Whilst an association between increased levels of alcohol consumption and increased pulmonary function seems a peculiar finding upon face value, it could once again be due to the fact that increased alcohol consumption could be an indication of a more socially active lifestyle.

The last model, model 10, addresses what degree of variation in Pulse can be explained by our three behavioral variables of interest. Intriguingly enough, the multivariate regression for pulse has overall less statistically significant coefficient's than the aforementioned multivariate regressions on BMI and Pulmonary Function, in addition to this the effects appear to be of smaller magnitudes. Specifically, smoking appears to increase an individual's pulse by, on average, 2 beats per minute and this result is statistically significant at the 10% significance level. Further, drinking an additional day during the week surprisingly appears to decrease an individual's pulse by approximately 0.15 beats per minute, so negligibly, and this result is in fact not statistically significant. However, at the 5% significance level, there is support to suggest that decreased frequency of exercise results in an increased pulse.

Table 7: The effect of behaviors on physical health measures

	BMI	Pulmonary Function	Pulse
	(1)	(2)	(3)
Drinking	-0.4292***	4.7995**	-0.1490
	(0.0910)	(1.8762)	(0.1810)
Exercise	0.6171***	-8.0274**	0.8347**
	(0.2023)	(4.0866)	(0.3919)
Smoking	-2.7382***	-40.851***	2.0508*
	(0.5627)	(11.720)	(1.1145)
No. of obs	658	658	658

Note: This table reports estimated coefficients for behavioral variables, on individual physical health measures, the results summarised in this table are captured by Models 8, 9, and 10. Column (1) captures the effects of drinking alcohol, partaking in light exercise, and smoking cigarettes on an individual's BMI. Column (2) captures the effects of drinking alcohol, partaking in light exercise, and smoking cigarettes on an individual's Pulmonary Function. Column (3) captures the effects of drinking alcohol, partaking in light exercise, and smoking cigarettes on an individual's Pulse. Across all multilinear regressions, the same sample consisting of 658 individuals is utilized. Heteroskedasticity and autocorrelation consistent (HAC) standard errors are reported in brackets whereas the p-value is expressed as: $(***)$ $p < 0.01$; $(**)$ $p < 0.05$; $(*)$ $p < 0.10$.

7 Discussion & Conclusion

7.1 Conclusions

Does living in a better area positively influence individual health outcomes? In order to address this question, this thesis focuses on movers and exploits the time relative to their move, in order to empirically test whether moving to a better (or worse) area has effects on Self-Reported Health and physical health measures. Through the application of fixed-effects analysis initially, Self-Reported Health is investigated, followed by three physical health measures including, BMI, Pulmonary Function, and Pulse. Finally, to supplement this analysis, three behavioral variables are investigated in a similar manner in order to add additional depth to the results and to establish if subsequent changes in health outcomes, postmove, may be a result of behavioral changes triggered by exposure to a new (better or worse) environment.

Within this paper, it is illustrated that individuals who moved to a better environment, with lower levels of income inequality, were approximately 9.6%, and 7.2% more likely to report themselves as having good Self-Reported Health one period, and two periods after moving respectively. However, there was no evidence to suggest that individuals who moved to a worse environment experienced any statistically significant changes, positive or negative, in their Self-Reported Health. Similarly, there was no evidence to suggest that individuals, regardless of whether they moved to an area with lower (or higher) levels of income inequality, experienced any subsequent changes in their BMI, Pulmonary

Function, or Pulse. Suggesting, that the improvements in Self-Reported Health across movers who moved to a better area may not be indicative of actual improvements in health but rather an indication of their improved perception of their health. This is supportive of the findings presented in Fiscella and Franks (2000), which suggested that whilst income inequality does appear to have marginal effects on self-reported health it does not appear to have effects on mortality and in fact, individual income appears to be much more influential on mortality and physical health measures than income inequality. When considering behavioral variables, interestingly, there was evidence to support decreased levels of light exercise, one-period post-move, across both those who moved to areas with lower and higher levels of income inequality. In addition to this, there was evidence to support decreased alcohol consumption amongst individuals who moved to a better environment, however, moving appeared to have no effect on an individual's likeliness to smoke irrespective of whether they made a good or bad move.

The implications of these results for policymaking are somewhat unclear. Whilst, there is evidence to suggest that relocating to a better environment, with lower levels of income inequality, results in an increased likelihood that individuals report their self-reported health as good, there appears to be no evidence that this results in improvements in physical health measures. In addition to this, there appears to be no evidence that suggests that moving to a worse region, with higher levels of income inequality, results in worse self-reported health or physical health measures. Pickett and Wilkinson (2015) suggest that one of the largest explanations, they see, for the evident link between income inequality and health is the increased social gradients that come with income inequality, which in turn exacerbate the effects of differences in social classes. Thus, it could be that whilst lower levels of income inequality may be a good indicator of a socially cohesive environment that perhaps high levels of income inequality do not necessarily act as a proxy for more socially polarized environments. Nonetheless, there is a large body of literature that delves into the evident link between income inequality and health outcomes, of which most find that health typically tends to be worse in more unequal societies (Lynch et al. (2004); Macinko et al. (2003); Wagstaff and Van Doorslaer (2000)). Therefore, it is imperative when focusing on addressing health inequities, that policymakers consider the implications and lean more on tools such as redistributive tax policies, and additionally help to incentivize corporations to reduce income differences before taxation.

7.2 Limitations

When assessing the potential limitations of, and threats to, this study design three main problems stand out. The first one being the sample size. The fixed-effects regressions, denoted by models 1-7, were conducted on modest samples including 314 individuals in the good move sub-sample and 344 individuals in the bad move sub-sample. This is primarily due to a lack of data, given that this study chose to focus on individuals who moved region of residence throughout the duration of the study this immediately narrows down the sample significantly as most individuals within the sample did not move at all. This can be seen by addressing Table 8, in the appendix, where the number of observations for most physical measures across those that did not move at all sits at approximately 24,000 and drops to around 1,000 for those that have moved once. In addition to this, the extended face-to-face portion of the interview, with which RAND collects data points on bio-markers, is only performed on a selected sample of individuals. Given that this paper was also interested in investigating the effects of moving on physical health measures, this also resulted in a limited sample size. Although a larger sample size would have been preferred, given that the sample is representative of the target population, it is believed that this smaller sample size can still be used to provide meaningful insights and that its size does not hinder the external validity of this study.

Secondly, this study relies on the implicit assumption that the exposure to neighborhood effect is compounding in nature. Previous literature found, after moving to a better neighborhood, children's life outcomes improved linearly in proportion to the amount of time a child spent growing up in that area, at a rate of approximately four percent per year of exposure (Chetty et al. (2016a)). This evidence suggests that neighborhood exposure effects are indeed compounding in nature; however, it remains unclear whether neighborhood effects influence adult outcomes in the same manner.

The final concern regards the size of the regions, as mentioned in the data section. The data categorized the US into nine distinct regions. Although throughout this paper we reference estimating neighborhood effects, or local area effects, the neighborhoods, or local areas, consist of regions that are defined explicitly in Table 1. Thus, these "neighborhoods" are not neighborhoods in the traditional sense but instead are more populous regions that consist of between three states, in the Middle Atlantic Division, all the way up to nine states, in the South Atlantic Division. Using such large areas can be a cause of concern, as it can elicit problems such as aggregation bias and attenuation bias. The main reason why we have opted to use such large areas is primarily due to data availability, data at the zip-code level is not as readily available nor easily accessible. In addition to this, data on health outcomes at an individual level is relatively poor – thus using larger regions will allow us to study the effects of one's neighborhood on such individual health outcomes. Furthermore, in the research conducted by Chetty and Hendren (2018), they opted to characterize neighborhoods as commuting zones, which they described as aggregations of counties based on commuting patterns in the 1990 census constructed by Tolbert and Sizer (1996). In fact, Chetty and Hendren (2018) only included commuting zones with over 250,000 residents within their model which again is considerably larger than the typical neighborhood. This did not appear to have any negative implications for their research, and they were still able to successfully estimate childhood exposure effects and their qualitative conclusions remained robust to alternative specifications (Chetty and Hendren (2018)).

7.3 Suggestions for Further Research

This research could be supplemented through the addition of auxiliary analysis. Specifically, it would be interesting to investigate whether the subsequent changes in Self-Reported Health, physical measures, and behavioral habits are similar across both males and females or whether they respond differently to exposure to a new environment. For example, are women more likely than men to pick up healthy habits, or cease unhealthy habits, upon exposure to a better environment, or vice-versa? This could help better our understanding of the differences between women's and men's average life expectancies.

Particularly because, whilst there is substantial evidence to suggest biological differences between women and men result in women having lower cardiovascular risks than men (Eskes and Haanen (2007)), this is accentuated by the increased likelihood amongst males to smoke cigarettes (Waldron and Johnston (1976)). Although the potential gender-based differences in exposure effects across self-reported health, physical health, and behavioral variables were of interest, given the limited sample size which was previously discussed, it was decided not to investigate this within this paper because of the further implications it would have on the sample size.

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8 Appendix

Table 8: Summary Statistics for Health Outcomes and Control Variables Across No. of Moves

	N = 0				N = 1				N >1			
	Mean	Median	Std. Dev	No. Obs	Mean	Median	Std. Dev	No. Obs	Mean	Median	Std. Dev	No. Obs
BMI physical measure	29.83	29.00	6.23	23,318	29.80	29.17	5.95	1,209	29.60	28.93	5.58	231
Pulse	71.02	70.17	10.61	24,116	70.40	69.67	10.26	1,251	71.37	70.78	10.04	239
Pulmonary function	365.39	353.33	133.23	24,118	367.15	355.00	129.34	1,251	378.67	360.00	131.61	241
Self-reported health	3.00	3.00	0.98	29,538	2.91	2.86	0.95	1,467	2.87	3.00	1.00	2.68

Note: Summary statistics over individuals who moved never, once and more than once. The number of moves is denoted as N, where $N \in \{0, 1, > 1\}$.

Table 9: Summary Statistics for Behavioural Variables Across No. of Moves

		N = 0			N = 1			N >1		
		%	Cum. %	Count	%	Cum. %	Count	%	Cum. %	Count
Frequency of light	(1) Everyday	3.3	3.3	972	3.2	3.2	47	2.6	2.6	7
exercise	(2) >1 time / week	47.9	51.2	14164	49.1	52.4	721	48.9	51.5	131
	(3) 1 time / week	26.5	77.7	7826	28.9	81.3	424	36.9	88.4	99
	(4) 1 - 3 times / month	14.5	92.2	4293	14.1	95.4	207	9.7	98.1	26
	(5) Never	7.8	100.0	2290	4.6	100.0	68	1.9	100.0	5
Smoking status	(0) No	84.8	84.8	24918	85.1	85.1	1238	80.1	80.1	214
	(1) Yes	15.2	100.0	4469	14.9	100.0	217	19.9	100.0	53
No. of days / week	(0) Never	61.2	61.2	18064	53.2	53.2	780	50.0	50.0	134
alcohol is consumed	(1) 1 day / week	14.0	75.2	4150	17.2	70.3	252	16.8	66.8	45
	(2) 2 days / week	9.4	84.6	2776	10.0	80.3	146	10.1	76.9	27
	(3) 3 days / week	4.3	88.9	1266	5.7	86.0	83	9.3	86.2	25
	(4) 4 days / week	3.9	92.8	1160	4.7	90.7	69	4.1	90.3	11
	(5) 5 days / week	2.2	95.0	646	3.5	94.1	51	3.7	94.0	10
	(6) 6 days / week	2.3	97.3	690	2.8	96.9	41	2.2	96.3	6
	(7) 7 days / week	2.7	100.0	788	3.1	100.0	45	3.7	100.0	10

Note: Summary statistics across behavioural variables for individuals who have never moved, moved once, and more than once. The number of moves is denoted as N, where $N \in \{0, 1, > 1\}$. The statistics are offered as a count of individuals falling in each category, the percentage of the sample falling in each category, and the cumulative percentage, denoted as count, %, and Cum. %, respectively.

Table 10: Breusch-Pagan Test of Homoscedasticity Results

	Bad move		Good move	
	Statistic	Sig.	Statistic	Sig.
Model 1: Self-Reported Health	8.984	0.174	9.733	0.136
Model 2: BMI	11.764	0.067	9.085	0.169
Model 3: Pulmonary Function	7.638	0.266	11.583	0.072
Model 4: Pulse	20.554	0.002	6.820	0.338

Note: This table summarizes the test statistic from the Breush-Pagan Test which was computed across all four samples for models 1, 2, 3, and 4 respectively. The Breush-Pagan test tests for the Homoscedasticity assumption, specifically if the p-value of the test statistic is lower than the chosen alpha level (0.05) the null hypothesis of homoskedasticity is rejected, and heteroskedasticity assumed

Table 11: Shapiro-Wilk Test of Normality Results

	Bad move		Good move	
	Statistic	Sig.	Statistic	Sig.
Model 1: Self-Reported Health	0.979	0.000	0.976	0.000
Model 2: BMI	0.972	0.000	0.970	0.000
Model 3: Pulmonary Function	0.985	0.000	0.991	0.018
Model 4: Pulse	0.985	0.000	0.966	0.000

Note: This table summarizes the test statistic from the Shapiro-Wilk Test which was computed across all four samples for models 1, 2, 3, and 4 respectively. The Shapiro-Wilk test tests for the Normality assumption, specifically if the p-value of the test statistic is lower than the chosen alpha level (0.05) the null hypothesis is rejected, implying that there is evidence that the data tested are not normally distributed.

Table 12: Ramsey RESET Test of Linearity Results

	Bad move		Good move	
	Statistic	Sig.	Statistic	Sig.
Model 1: Self-Reported Health	4.357	0.037	2.379	0.123
Model 2: BMI	0.000	0.990	3.836	0.050
Model 3: Pulmonary Function	3.026	0.082	1.141	0.286
Model 4: Pulse	3.119	0.077	10.168	0.001

Note: This table summarizes the test statistic from the Ramsey RESET Test which was computed across all four samples for models 1, 2, 3, and 4 respectively. The Ramsey RESET test tests for the Linearity assumption, specifically if the p-value of the test statistic is lower than the chosen alpha level (0.05) the null hypothesis is rejected, implying that there is evidence that the model suffers from misspecification.

Table 13: Durbin-Watson Test of Independence Results

	Bad move	Good move
Model 1: Self-Reported Health	1.069	1.243
Model 2: BMI	1.419	1.587
Model 3: Pulmonary Function	1.539	1.288
Model 4: Pulse	1.502	1.703

Note: This table summarizes the test statistic from the Durbin-Watson Test which was computed across all four samples for models 1, 2, 3, and 4 respectively. The Durbin-Watson test tests for the Independence assumption, the Durbin-Watson test statistic ranges from 0-4, d=2 indicates that there is no autocorrelation and therefore that the independence assumption is fulfilled. Generally, as a rule of thumb, if the Durbin-Watson test statistic is below 1, there may be a cause for concern.

Table 14: Variance Inflation Factor Test of Multicollinearity Results

	Relative Year	Age	Income	R.Emp	R.Educ	R.Inc
Bad move						
Model 1: Self-Reported Health	1.182	1.101	1.094	1.207	1.348	1.454
Model 2: BMI	1.156	1.118	1.092	1.316	1.422	1.450
Model 3: Pulmonary Function	1.155	1.108	1.100	1.295	1.400	1.434
Model 4: Pulse	1.169	1.114	1.095	1.309	1.400	1.426
Good move						
Model 1: Self-Reported Health	1.085	1.108	1.086	1.231	1.399	1.394
Model 2: BMI	1.114	1.099	1.092	1.336	1.460	1.451
Model 3: Pulmonary Function	1.116	1.107	1.093	1.302	1.456	1.430
Model 4: Pulse	1.105	1.110	1.092	1.321	1.460	1.438

Notes: This table summarizes the test statistic from the Variance Inflation Factors which were computed across all four samples for models 1, 2, 3, and 4 respectively. The Variance Inflation Factors test for the Multicollinearity assumption, generally as a rule of thumb if Variance Inflation Factors are greater than 5 then multicollinearity is high (a threshold of 10 is often also used).

Table 15: Wald Test of Joint Significance of Explanatory Variables

	Good Move	Bad Move
Model 1: Self-Reported Health	4.153**	0.612
Model 2: BMI	0.271	0.381
Model 3: Pulmonary Function	0.047	0.763
Model 4: Pulse	0.581	1.188
Model 5: Drinking	6.456***	2.852*
Model 6: Exercise	0.179	0.151
Model 7: Smoking	2.368	1.528

Note: The Wald test was conducted on Models 1 - 7, in order to test the joint significance of the explanatory variables of interest. Specifically, the Year Relative to Move variables including T-1, T+1, and T+2. The p-value is expressed as: $(***)$ p <0.01; $(**)$ p <0.05; $(*)$ p <0.10.