Niels van Opstal 24-1

**Please add something on the ceiling effect i.e. you are so close to perfect health that it is very hard to improve anything.**

**Abstract:**

This paper tries to find a causal relationship from wealth to health in the Netherlands using a difference in differences analysis and an analysis that focuses on negative health transitions. Ttreatment used for the difference in differences analysis is the sudden drop and bounce back in housing prices caused by the financial crisis. The treatment group consists of people who own a house and the control group consists of people who rent a house. This makes the net wealth of the treatment group more responsive to the change in housing prices than the net wealth of the control group. In the analysis that focuses on health transitions only negative health transitions are taken into account since the average health found was nearly perfect. This study uses self-assessed health as the health variable. The data used consists of 3 waves from the Dutch Household Survey. The study found no evidence of a significant causal effect of wealth on health in the short run.

# Introduction:

The positive correlation between health and wealth has been shown many times. Pollack et al. (2007) for example found 29 studies that tested for the correlation between health and wealth. But “since most of the studies identified were cross-sectional, causal inferences cannot be made” (Pollack et al., 2007, p. 263). Health and wealth could easily be endogenous. Wealth could affect health through better access to health care and better living conditions. Health could affect wealth through the ability to work and thus accumulate wealth. It could also be possible that for example time preference affects both the accumulation of wealth and health (Meer, Miller, & Rosen, 2003).

As Aittomäki, Martikainen, Laaksonen, Lahelma, and Rahkonen (2010) point out, “Wealth in particular is not directly affected by changes in labor market participation that may radically alter the current income level”. They find that wealth is highly relevant in explaining health.

Even though the correlation between health and wealth is researched a lot and a majority of these studies find positive results, the body of literature addressing the causality between health and wealth is smaller and finds mixed results. As Meer et al. (2003) point out, more research is needed on the subject of direction of causality between health and wealth. This is especially important for public policy since it cannot simply rely on correlations in this case.

The goal of this paper is to examine the causality between health and wealth in the Netherlands. Especially, this paper will try to find a causal relation from wealth to health. This paper will try to deal with the endogeneity between health and wealth in two ways. The first is using a difference in difference analysis. The second way this paper tries to deal with the endogeneity is by focusing on the effect of wealth on health transitions.

In the difference in differences analysis, the treatment group consists of home-owners and the control group consists of people who rent a house. Two different treatments will be used. First, the financial crisis in 2008 as it affected housing prices and secondly the bounce-back of the housing prices after the financial crisis. The change in housing prices should affect the net wealth of the home-owners more than the net wealth of tenants since the wealth of home owners is more exposed to changes in housing prices than the wealth of tenants. It stands to reason that the change in housing prices does neither directly affect health status nor are the housing prices directly affect by health. So if there is a causal effect from wealth to health, the health of the home owners should thus react differently to the change in housing prices than the health of the tenants. In this paper, health is dummy variable where a person is either healthy or unhealthy, based on their self-assessed health.

In the second analysis where this paper tries to estimate the effect of wealth on health transitions, health is defined in the same way as in the difference in differences analysis. Because this analysis focusses on health transitions rather than health status itself, it deals with the possible endogeneity between wealth and health. Wealth is defined as the net wealth of a person, i.e. all his assets minus all his debts.

To examine causal relationship between health and wealth, this study uses the data from the DNB Household Survey (DHS) from CenterData. This dataset allows to study both the psychological as well as the economic aspects of financial behavior. The data has information of health, housing, possessions among other thing. (“DHS data access | CentERdata.nl,” n.d.). The survey tries to get as many recurring respondents as possible and adds new respondents when needed to make the average number of respondents around 2000. Using different waves of this dataset will allow this paper to try and find a causal relationship using the difference in difference analysis.

The paper will be structured as follows. The first chapter will discuss relevant literature on the subject of causality between health and wealth. The second chapter will briefly

Describe the institutional setting in the Netherlands. The third chapter will describe the data and the variables used in this study. The fourth chapter will describe the different statistical methods used. Here, the methods for identifying the correlation and causal relationships between wealth and health will be further discussed. The fifth chapter presents the results of the statistical analyses. The sixth chapter will present results from different robustness tests and the final chapter will conclude this paper and present some improvements and ideas for further research

# Related literature:

In their article *Should Health Studies Measure Wealth*, Pollack et al. (2007) systematically analyze a total of 29 articles that used health as the dependent variable and wealth and at least one other socioeconomic-status variable as independent variables. Of the 29 articles analyzed, 14 used self assed health as their health variable. Most of those articles reported positive or mixed results. The other 15 articles used different variables for health such as: mortality, chronic conditions, functional status and mental health. Of the total of 29 studies, 15 found positive results, 10 found mixed results and only 4 found negative results. They conclude that there is a significant correlation between health and wealth. The correlation between health and wealth was most significant when the wealth variables were constructed from detailed questions instead of simpler questions (for example just a single question). It should however be noted that they only check for correlations and do not address causality.

There are however some studies that do address causality in the health wealth connection and some find insignificant causal effects. Meer et al. (2003) use a straightforward instrumental variable strategy to deal with the endogeneity. They use inheritance as the instrument because, they reason, it does affect health but does not directly affect health nor is it affected by health. They do not find a significant effect from wealth on health by using inheritance as the instrument variable. They conclude that short run changes in wealth do not affect health. They do however note: “This finding does not rule out the possibility of a long-term impact of wealth on health” (Meer et al., 2003, p. 729). Kim and Ruhm (2012) also use inheritance as exogenous wealth shocks and also find no significant effect on health. Au and Johnston (2015) even find that wealth shocks in the form of inheritance might even increase obesity in women. As obesity is an indicator of not so good health, this result is surprising as it contradicts the positive correlation between wealth and health. What about the correlation between genes and inherentences? It seems that there exclusion restriction is trivially violated.

Apouey and Clark (2015) also find small or negligible effects on general health using lottery winnings and inheritance as instruments. They do however find that lottery winnings do produce better mental health but also increase smoking and social drinking. They note that “health is not a holistic concept, and we need to both be clear about what kind of health we are talking about and be ready for the possibility that different types of health behave in very different ways” (p. 536).

It could however be argued that inheritance might not be a good instrument to find a causal effect in this case. Most people will know whether or not they will inherit something. Because people know they will inherit something it will not come as a truly exogenous wealth shock. They will make their decisions prior to receiving the inheritance with the inheritance in mind, therefore it could have an effect on health before the inheritance is inherited . Since winning the lottery is less predictable, lottery winnings might be a better instrument in this case.

Michaud and Soest (2008) also find no causal effects of wealth on health. They use a dynamic panel data model to test for the causality. As they note in their conclusion, the data they use consists only of elderly couples. They suggest that there might be a causal effect in different age groups and that it would be interesting to see if there are differences between countries to see if institutions have an impact on the possible causal relationship.

There are studies that do find a significant causal effect of wealth on health. Cai (2009), for example, focuses on health transitions instead of health status itself to avoid the endogeneity of wealth and health. She finds that wealthy people are less likely of transitioning from healthy to unhealthy compared to people in the lower end of the wealth distribution in Australia. This, she argues, is evidence that there might be a causal effect of wealth on health in Australia. She proposes four different explanations of the causal effect of wealth on health. Firstly, because the study focuses on people in Australia malnutrition might not be an issue but eating less healthy food is associated with people with less economic recourses such as wealth or income. Secondly, people with more wealth may live in better and healthier environments. Thirdly, even in a country with universal health care system such as Australia, wealthier people might still receive more health services that less wealthy people. Finally, wealth could give people more freedom in making decisions, thus experiencing less chronic stress which leads to poor health. So there are several ways in which wealth could exert an effect on health. Testing via which effect wealth does affect health was out of the scope of her paper. This study also focusses on whether or not there is a causal effect rather than trying to explain through which channel this causal effect might happen.

Keese and Schmitz (2014) find a significant causal effect between indebtedness and worse physical and mental health. They control for the unobserved heterogeneity between health and indebtedness by using fixed-effects methods and also a subsample of constantly employed individuals plus lagged debt variables. By using those methods they reduce the problem of the endogeneity. Although they do not search for a causal relationship between wealth and health, debt is part of net wealth which is the interest of this paper.

This paper contributes to the current literature in two ways. Firstly, after a thorough search for literature another paper that uses a difference in differences analysis using the change in housing prices caused by the financial crisis to estimate the causal effect from wealth to health has not been found. Secondly, this paper extends the method used by Cai (2009) in which she uses health transitions to estimate the causal effect of wealth on health to data from the Netherlands.

# Institutional section:

As Michaud and Soest (2008) pointed out, differences in institutions between countries might have an impact on the relationship between wealth and health. Since the data consists of respondents from the Netherlands it is important to look at Dutch institutions setting. There are two key features of Dutch institutional context that might impact the relationship between health and wealth: the obligated health insurance, the paying of salary for a sick person with and without a permanent contract.

In the Netherlands, every Dutch citizen is obligated to have a health insurance. There is a basic insurance and the possibility to buy additional insurances which increases coverage. With the basic insurance all visits to the family physician are covered and if you are treated with a referral from the family physician, most of the referred treatments are covered as well. There also is a mandatory yearly deductible which is set at a minimum of €385 (Eigen risico. Wat is het en waarom betaalt u het? - Zilveren Kruis, 2009) and a maximum of €885. The person who buys the insurance can set his own deductible somewhere between those values and it can be argued that the rational individual who has poor health will always set their deductible as low as possible. Someone can also receive a health insurance subsidy, if you are eligible. Whether or not a person is eligible depends on the income of that person. The maximum income to receive the subsidy is €29,562 for a single person and €37,885 for a couple (Belastingdienst, 2018). Therefore, everyone has, and can afford, an health insurance.

The other feature is the paying of salary when you are sick. If someone is sick and has a permanent contract he gets payed at least 70% of their salary in the first year of being sick, whether a person is sick for a week or a year. Someone could receive more than 70% if specified in his or her contract . If 70% of the salary is below the minimum loan, they get payed at least the minimum loan in the first year. In the second year of being sick, at least 70% of the salary is continued to be paid but it can be less than the minimum loan. If a person does receive less than the minimum loan in the second year he can apply for a benefit which makes the total income equal to the minimum year. (UWV, n.d.) When a person without a permanent contract gets sick, salary will continue to be paid for the duration of the contract. When someone is still sick when the contracts ends, he or she can possibly get a benefit (Het Juridisch Loket, n.d.). Overall, someone who has an income from working but is unable to keep working due to poor health will keep roughly the same income. And will not impact wealth (at least in the short run)?

Since every Dutch person will have an insurance, a causal effect from health to wealth is less likely in the Netherlands than in other countries where not everyone has a health insurance. The reason for that is the fact that the negative health shocks caused by treatment of a disease or hospital care are being paid by the insurance. Therefore the negative wealth shock of for example hospital treatment is almost non-existent. [Good, also mention this in the introduction and the discussion on why the literature find different effects.]

Also, because an income is not lost when a person is unable to work due to health problems a causal effect from health to wealth is less likely to exists in the Netherlands. Because someone keep an income when they are unable to work due to poor health, wealth is less likely to be impacted by bad health in the short run. You forget about job changes and/or wage increases. Also because the height of the benefit depends on the income before a person gets sick, people do not only keep an income but also an income which is in line with their income before becoming sick.

Hurd and Kapteyn (2005) also point there are “generous income maintenance provisions [that] aim to mitigate any adverse effect of health related earnings interruptions” (Hurd & Kapteyn, 2005, p. 311) in the Netherlands. They add to this that since healthcare is basically universal, the explanation that different access to healthcare is due to differences in wealth or income is of limited importance.

# Data

The data consists of different (yearly) waves from the DHS. The data is collected every year by the CenterData. The DHS consists of six questionnaires, General Information on the Household, Household and Work, Accommodation and Mortgages, Health and Income, Assets and Liabilities and Economic and Psychological Concepts. (“DHS data access | CentERdata.nl,” n.d.) Besides the questionnaire data, the CenterData also provides two aggregated data files, the aggregated income data and the aggregated wealth data. This paper will only use the Health and Income questionnaire which includes the self-rated health variable and the aggregated wealth data. The aggregated wealth data is made up from different questionnaires and consists of all the assets and liabilities someone might have.

The health variable is a categorical variable with two options, either healthy (1) or not healthy (0). The data received from the DHS has five categories for health: poor, not so good, fair, good and excellent. People were placed in one of these categories by self assessment. Self assessed health is a good predictor for mortality (Idler & Benyamini, 1997) which is a good indicator for health. Individuals who considered themselves to be in poor or not so good health are placed in the not healthy category. The persons that consider themselves to be in fair, good or excellent health will be placed in the healthy category.

In this paper, wealth is defined as the net wealth of a person. Someone might well own a nice car and a house, but if he has a loan for the car and two mortgages on the house, he might still have a negative net wealth. To calculate the net wealth, all the assets of a person have been added together and the liabilities have been subtracted from the assets. The questionnaires are quite detailed on wealth which is important as was pointed out by Pollack et al. (2007).

The assets and liabilities that could be found in the aggregated wealth data and of which the net worth variable consists of can be seen in table 1.

Table 1 Assets and liabilities of which net worth is made up off

|  |  |
| --- | --- |
| Assets | Liabilities |
| checking accounts | private loans |
| employer-sponsored savings plans | extended lines of credit |
| savings or deposit accounts | outstanding debts not mentioned earlier |
| deposit books | finance debts |
| savings certificates | loans from family or friends |
| single-premium annuity insurance policies | study loans |
| savings or endowment insurance policies | credit card debts |
| growth funds | loans not mentioned before |
| mutual funds and/or mutual fund accounts | checking accounts with negative balance |
| bonds and/or mortgage bonds |  |
| stocks and shares |  |
| put options bought |  |
| put options written |  |
| call options bought |  |
| call options written |  |
| pieces of real estate, not being used for own accommodation |  |
| value of life insurance mortgage real estate |  |
| cars |  |
| motorbikes |  |
| boats |  |
| (site-)caravans/trailers |  |
| money lent out to family or friends |  |
| savings or investments not mentioned before |  |
| stocks from substantial holding |  |
| business equity (professions) |  |
| business equity self-employed |  |
|  |  |

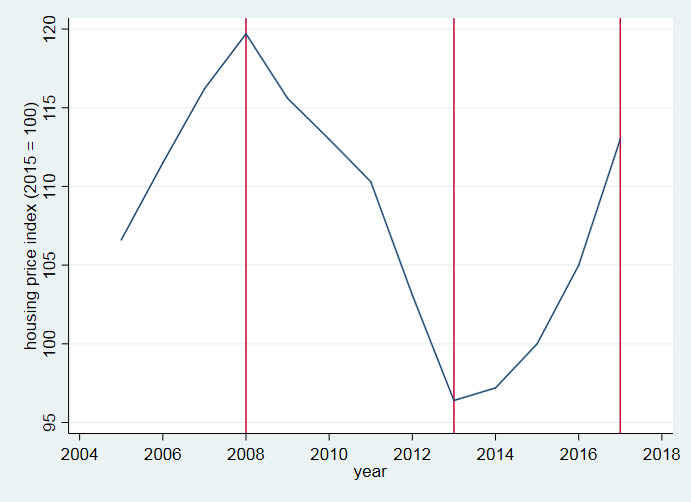


Figure 1 Housing Prices in the Netherlands. (CBS, 2019)

This paper uses the waves from 2007, 2013 and 2017. As is clearly visible in figure 1, the housing prices peaked somewhere in 2008. Because the data is collected throughout the whole year it makes sense to take 2007 as the pretreatment year. Because the financial crisis hit in September 2008 it might have affected some observations while others not. 2013 is the year when the housing prices were at the lowest in the Netherlands. If wealth would cause short-term changes in health, it should be visible in the difference in differences regression 2007 – 2013 and 2013 - 2017. So in the first case, 2007 is the pre-treatment year and 2013 the post-treatment year. In the second case, 2013 is the pre-treatment year and 2017 the post-treatment year. Because in the DD analysis the treatment is the effect of the difference in housing prices, housing prices of single years will be used instead of averages. When for example the average housing prices of 2004 until 2007 will be used and the average housing prices of 2009 until 2013, the difference between the two averages will almost completely be canceled out against each other. This will make the effect of the change in housing prices less noticeable on the net wealth.

For the analysis that uses health transitions the same years will be used as in the difference in differences analysis. Since changes in health are not likely to happen over a short time span as for example a year, as was noted above, a five year timespan could be enough for changes in health to happen. It also makes sense to use the same years as the DD analysis since it allows to compare the results of both regressions.

Table two shows the number of observations per year and the size of the treatment group, consisting of home-owners and the control group, consisting of tenants. In all the three years the ratio of treatment group to control group is rather consistent and lies around 1:1.

Table 2 distribution of individuals in the all observations sample

|  |  |  |  |
| --- | --- | --- | --- |
| Year | size treatment group | size control group | Total observations |
| 2007 | 835 (46.14%) | 974 (53.84%) | 1809 |
| 2013 | 807 (48.94%) | 842 (51.06%) | 1649 |
| 2017 | 1161 (52.42%) | 1054 (47.58%) | 2215 |

Also add maybe somewhere else, what you gain from a repeated cross section and what you gain from a panel.

Table 3: Distribution of individuals in the recurring individuals sample

|  |  |  |  |
| --- | --- | --- | --- |
| period | size treatment group | size control group | Total observations |
| 2007-2013 | 374 (53.20%) | 329 (46.80%) | 703 |
| 2013-2017 | 504 (58.27%) | 361 (41.73%) | 865 |

Table three shows the summary statistics of respectively 2007, 2013 and 2017. In all of the three years both the control and treatment group have a fairly high chance of being healthy but the treatment group has a slightly higher chance of being healthy. In the treatment group of 2007, 97% of the people are healthy, in 2013 and 2017 that is 96%. In the control group 95% of the people observed are healthy in 2007 and 2013 and 92% of the people are healthy in 2017. Since the means of the health of both groups are within range of the standard deviations, it can be noted that there is no significant difference between health in the treatment and control group in any of the years.

The average net worth of the treatment group decreases between 2007 and 2013 and then increases between 2013 and 2017. The average net worth of control group increases between 2007 and 2013 and also between 2013 and 2017. Since the house prices also decrease between 2007 and 2013 and increase between 2013 and 2017 this indicates that the average net worth of home owners does behave in line with the housing prices while the net worth of the tenants does not, as was expected.

Table 4: summary statistics 2007 (Deze zijn al netjes gemaakt in LaTeX)

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Treatment group | Mean | Standard deviation |
| Health | Yes | 0.97 | 0.18 |
|  | No | 0.95 | 0.22 |
| Net worth | Yes | 275,271 | 329,037 |
|  | No | 25,400 | 75,946 |

Table 5: summary statistics 2013

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Treatment group | Mean | Standard deviation |
| Health | Yes | 0.96 | 0.20 |
|  | No | 0.95 | 0.22 |
| Net worth | Yes | 256,521 | 249,175 |
|  | No | 28,933 | 91,215 |

Table 6: summary statistics 2017

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Treatment group | Mean | Standard deviation |
| Health | Yes | 0.96 | 0.18 |
|  | No | 0.92 | 0.27 |
| Net worth | Yes | 263,053 | 291,670 |
|  | No | 31,530 | 102,177 |

# Methods

In this section I discuss the three methods employed in this paper. First the ordinary least squares regression is briefly discussed which is used to show the correlation between wealth and health. Secondly the difference in differences analysis is discussed. Finally, the analysis that uses health transitions is discussed briefly.

## OLS

First this paper will use a simple ordinary least squares (OLS) regression. In this OLS regression health will be the dependent variable and wealth will be the independent variable. Health is defined as a categorical variable where someone can be either healthy, with value 1, or unhealthy, with a value of 0. Wealth is the net worth of a person as shown above.

## Difference in differences

Secondly, this paper uses a difference in difference (DD) analysis to look for a causal effect from wealth to health. Health is defined in the same way as in the OLS regression. A DD analysis is a quasi-experimental design with a treatment group, a control group and a treatment. A DD analysis is used to estimate the effect of a treatment by comparing the differences in the outcomes between before and after the treatment between the treatment and the control group.

The treatment group, control group and the treatment itself will be defined as follows. The treatment this paper uses is the financial crisis of 2008 in which housing prices dropped suddenly and sharply as is visible in figure 1. Another treatment that will be used is the bounce-back of the housing prices after the financial crisis which started in 2013. It can be assumed that the health of people did not directly cause the financial crisis, or that health was directly affected by the crisis. The treatment group consists of people who own one or more houses and the control group consists of people who rent a house. Although the net worth of tenants might also have been impacted in the years after the financial crisis, the home owners are exposed more to a wealth shock due to the change in housing prices. Therefore the net wealth of the control group should be affected less than the net wealth of the treatment group by the changes in the housing prices.

There is another way in which the financial crisis might have affected the health of the treatment and control group in a different way, namely through job loss. It is possible to think that renters are more likely to have a lower income and therefore perhaps have more short term contracts than home-owners. Also because getting a mortgage requires a steady flow in income. Individuals with short-term contracts are more prone to losing their job because of changes in business cycles and losing a job could cause stress which could result in poor health. This is however tested in the robustness section which showed that there is no significant different change in unemployment rate between the control and treatment group.

Regressions will be done on two different groups of observations, one group will consist of all observations and the second group will consist only on the same persons observed before and after the treatment. There is a difference in those groups because even though the survey tries to get the same people every year to fill it out, it does of course not have a perfect return rate of the respondents. Because the first group, the all-observations group, is bigger, the estimations should be better. For certainty, the second group, the recurring individuals group, is added which should show the same results as the first group.

Since the participants of the DHS are randomly selected, it can be assumed that the only real difference between the control and treatment group is the ownership of a house. In the all-observations group it is however possible that the characteristics of the control and treatment group change between the pre- and posttreatment period which could then cause differences in the differences in health between the two groups. This is tested in the robustness section which shows that apart from gender in the 2013 – 2017 period, the characteristics, such as job loss, education and net income, of the groups did not change differently in the treatment period. Therefore, the other ways in which the financial crisis could have affected health, for example through job loss, should be roughly the same in both the treatment and the control group. This means that the all-observations group is a valid group for the DID method even though not all people are recurring individuals pre and post treatment. In the recurring individuals sample, the characteristics matter less as they should remain pretty much the same since it follows the same individuals. The characteristics are especially unimportant in the fixed effects regression.

The following regression model will be used for the difference in difference analysis:

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

Where is whether or not person i is healthy or not in period t. Time is whether an observation is pre or post treatment. Treated is whether a person is in the treatment or control group and Time \* Diff is the difference in change over time. If the Time \* Diff coefficient is statistically different from zero, there is an effect from the treatment on the dependent variable. The coefficients will be estimated with an OLS regression.

Therefore the hypotheses are:

|  |  |  |
| --- | --- | --- |
|  |  | (2) |
|  |  | (3) |

More specifically, is expected to be smaller than zero in the 2007 – 2013 regression since the housing prices decreased in this period and the health of the treatment group should therefore decrease more than the health of the control group. is expected to be greater than 0 in the 2013 – 2017 regression since the housing prices increased in this period and the health of the treatment group should therefore have increased more than the health of the control group.

To show that the difference in difference analysis will give the desired causal effect, let be the health of person *i*, in group *g* at period *t* if the person owns a house. Also, let be the health of person *i* in group *g* at period *t* if the person is a tenant. Here the group *g* is either the treatment group, i.e., home-owners (1) or the control group, i.e., tenants(0) and the period *i* is either before (0) or after the treatment (1).

Assume that:

|  |  |  |
| --- | --- | --- |
|  | . | (4) |

Equation 4 tells us that in absence of the sudden changes in housing prices caused by the financial crisis, the health of a person is equal to the sum of a time-invariant group effect ( and a time effect that is the same in both the groups ().

Let be a dummy for the interaction between home-owners and the period. Therefore it is only one when the group is home owners and the period is post-treatment. In the other three cases, is zero. Observed health, , can then be written as

|  |  |  |
| --- | --- | --- |
|  | , | (5) |

if it is assumed that , a constant. In equation (5), we get .

Therefore we get

|  |  |  |
| --- | --- | --- |
|  |  | (6) |

and

|  |  |  |
| --- | --- | --- |
|  |  | (7) |

Therefore, the population difference in differences is:

|  |  |  |
| --- | --- | --- |
|  | . | (8) |

Here δ is the causal effect of interest which is estimated through the model described in equation (1). The parameters in the model of equation (1) can be seen in the light of the model described in equation (5) in the following way:

|  |  |  |
| --- | --- | --- |
|  |  | (9) |

So is the sum of the time invariant group effect of the tenants and the time effect of the pre-treatment period. therefore it is the average health of the control group in the pre-treatment period.

|  |  |  |
| --- | --- | --- |
|  |  | (10) |

is the time effect of tenants group post treatment minus the time effect of the tenants post treatment. That is equal to the difference in the average health before and after the treatment.

|  |  |  |
| --- | --- | --- |
|  |  | (11) |

Therefore is the difference in the time invariant group effect between the home owners and tenants before the treatment. That is the same as to say the difference in average health before the treatment between the two groups.

|  |  |  |
| --- | --- | --- |
|  |  | (12) |

So this is the difference in differences between average health before and after the treatment of the home owners and the tenants.

### Extra characteristic variables

Because characteristics could differ and therefore explain some of the variation in health in the first group (i.e. all the observations) an extra regression on that group will be run which includes some extra variables. The extra variables are net income, education, unemployed and gender because they can all be assumed to have an effect on health. This is not necessary in the second group because these differences should cancel out between the pre-treatment and post-treatment periods. Because the extra variables are received from other surveys which are linked to the existing observations there are less observations when running this regression. This is because not everyone answers all the questions or surveys. The regression model will then look like this:

Where represents the extra coefficients. Net income is the net income reported by the data set in the aggregated income dataset. Education is a dummy variable where 1 represents highly educated and 0 not highly educated. Highly educated are people who have finished an education at the HBO level or university. Unemployed is also a dummy variable where 1 means unemployed and 0 means not unemployed. People who are unemployed are people who are looking for a job because they lost their last job or a looking for a job for the first time. Gender is a dummy variable as well where 1 represents male and 0 represent female.

### Fixed effects

To control for unobserved heterogeneity caused by time invariant characteristics (gender for example) in the same persons group, a fixed effects model is used. By using the fixed effect model, the time invariant characteristics of an individual that influence health are controlled for and therefore this model might produce better estimates. The model here is:

Where is the individuals intercept. This will cancel out in the fixed effects model regression, therefore reducing the error term.

## Health transitions

Thirdly, this paper uses an analysis which uses health transitions rather than health status. This method is based off the method used by Cai (2009). By focusing on health transitions the endogeneity between health and wealth is avoided. The transitions are measured between the same years which are used in the DD analysis. Therefore, there is one analysis which focusses on the transition between 2007 and 2013 and analysis which focusses on the transition between 2013 and 2017. This paper uses negative health transitions where a negative health transition is defined as the decrease in self-assessed health scale. People got to pick from *excellent, good, fair, not so good* and *poor* health which is the ordered form best to worst health. Only negative transitions are taken in account since the majority of the individuals analyzed reported that they are healthy in the base years, i.e., 2007 and 2013. Therefore, transition is a dummy variable where 1 stands for transitioned and 0 stands for no transition in health Characteristics that are used in the DD model in the all observations group are also used here. The model used for this analysis is therefore:

Where is whether or not a person decreased in health scale. stands for the net wealth of person i in the base year and are different characteristics of person i. The coefficients will be estimated by an OLS regression.

# **Results**:

## Basic OLS results

A simple OLS regression was conducted first to check whether or not there exists a correlation between health and health in this dataset. With the simple model:

The results of this regression can be seen in table 6. A significant (p < 5%) positive correlation between health and wealth was found as expected. Because health was defined as either healthy of unhealthy the regression tells us something about the chance of being healthy. According to the results a €1000 increase in net wealth corresponds with an increase of 2.81 percentage points to the chance of being healthy. Note that this correlation does not say anything about a possible causal effect.

Table 7 OLS results

|  |  |
| --- | --- |
| Intercept | 0.9476 |
|  | (0.000) |
| Net worth | 2.81 |
|  | (0.016) |
| F-statistic | 5.86 |
|  | (0.0155) |
|  | 0.0010 |

## Difference in Differences Analysis

As pointed out before in this paper, endogeneity is a problem when considering the causality of the effect of wealth on health. This study conducted a number of DID analyses to try to find a causal effect in the short-term of wealth on health. The first analyses the short term effects of wealth on health. It uses the waves from 2007 and 2013. The second analysis also analyses the short-term effect by using the 2013 and 2017 waves. The variable of interest is DID. If this variable is significant there is a significant difference in differences and therefore implies a causal effect from wealth to health.

The results from the analyses on the first group, i.e. all the observations, can be seen in table 7. The 2007 – 2013 regression does not have a significant DID. The 2013 – 2017 regression does have a significant (p < 5%) DID coefficient.

In the 2013 – 2017 analysis the time coefficient is -0.0291 which means that between 2013 and 2017 the average health of the tenants decreased by 2.9 percentage points. The DID is 0.0347 which means that the average health of the home owners increased 3.5 percentage points more than the average health of the tenants. The treated coefficient is insignificant indicating that at 2013, the average health of tenants and home owners was not significantly different.

When controlling for the other variables the significance of the DID coefficients that was significant disappears. Net income is however significant (p < 1%) which implies that the variation in health is partly explained by net income. This study tests in the robustness section if net income changed differently in the treatment period between the two groups to see if that could explain the difference in differences in health. The robustness test does not find a significant result. This implies that even though the variance in health in one year might be partly explained by income, the difference in the differences in health between the groups is not explained by net income rather than the change in housing prices caused by the financial crisis. Because the DID coefficient is insignificant in both years, this implies that there is no causal relationship between wealth and health in this group.

Table 8: DD results all observations

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | 2007 - 2013 | | 2013- 2017 | | | 2007- 2013 | | 2013- 2017 |
| VARIABLES | | health | | health | | | health | | health |
|  | |  | |  | | |  | |  |
| DID | | -0.0112 | | 0.0347\*\* | | | -0.0123 | | 0.0234 |
|  | | (0.0139) | | (0.0143) | | | (0.0155) | | (0.0155) |
| Time | | 0.0026 | | -0.0291\*\*\* | | | 0.0054 | | -0.0173 |
|  | | (0.0096) | | (0.0101) | | | (0.0110) | | (0.0113) |
| Treated | | 0.0190\*\* | | 0.0078 | | | 0.0173 | | 0.0028 |
|  | | (0.0096) | | (0.0108) | | | (0.0116) | | (0.0123) |
| Gender | |  | |  | | | -0.0124 | | -0.0110 |
|  | |  | |  | | | (0.0088) | | (0.0085) |
| Education | |  | |  | | | 0.0044 | | 0.0070 |
|  | |  | |  | | | (0.0084) | | (0.0082) |
| Net Income | |  | |  | | | 0.0000\*\* | | 0.0000\*\*\* |
|  | |  | |  | | | (0.0000) | | (0.0000) |
| Constant | | 0.9487\*\*\* | | 0.9513\*\*\* | | | 0.9426\*\*\* | | 0.9450\*\*\* |
|  | | (0.0065) | | (0.0076) | | | (0.0087) | | (0.0097) |
|  | |  | |  | | |  | |  |
| Observations | | 3,458 | | 3,864 | | | 2,586 | | 2,671 |
| R-squared | | 0.0013 | | 0.0060 | | | 0.0046 | | 0.0085 |
|  |  | |  | | |  | |
| \*\*\* p<0.01, \*\* p<0.05, \*p<0.1 | | | | |  | |  | |  |
|  | |  | |  | | |  | |  |
|  | |  | |  | | |  | |  |

The results from the regressions in the second group, so only observations of the same persons pre and post treatment, can be seen in table 8. There are no significant results for the DID variable. Therefore, there is no evidence that there is a causal effect from wealth on health in this group. Even though the error term is smaller in the results of the fixed effects model, the DID coefficient is still not significant.

The coefficient in the fixed effects regression are quite different from the non-fixed effects regression. This could imply that there are some time-invariant characteristics which could cause a different change in health that are not equally distributed between the control and treatment group. These time-invariant characteristics are canceled out in the in the fixed effects regression which could explain the differences in the coefficients between the two regression. This tells us that the fixed effect estimations will probably yield better estimations than the non-fixed effects estimations.

Table 9: DD results same persons

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | 2007 - 2013 | | 2013 - 2017 | | | 2007-2013 | | 2013-2017 |
| VARIABLES | | health | | health | | | health | | health |
|  | |  | |  | | |  | |  |
| DID | | -0.0207 | | 0.0099 | | | -0.0207 | | 0.0099 |
|  | | (0.0205) | | (0.0203) | | | (0.0166) | | (0.0146) |
| time | | -0.0061 | | -0.0139 | | | -0.0061 | | -0.0139 |
|  | | (0.0150) | | (0.0155) | | | (0.0121) | | (0.0112) |
| treated | | 0.0238 | | 0.0284\*\* | | | - | | - |
|  | | (0.0145) | | (0.0144) | | |  | |  |
| Constant | | 0.9574\*\*\* | | 0.9418\*\*\* | | | 0.9701\*\*\* | | 0.9584\*\*\* |
|  | | (0.0106) | | (0.0110) | | | (0.0058) | | (0.0051) |
|  | |  | |  | | |  | |  |
| Observations | | 1,406 | | 1,730 | | | 1,406 | | 1,730 |
| persons | |  | |  | | | 703 | | 865 |
| R-squared | | 0.0039 | | 0.0067 | | | 0.0082 | | 0.002 |
| Standard errors in parentheses | | | | | | |  | |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | |  | |  | |  |
|  | |  | |  | | |  | |

## Health transition analysis

The results of the regression on health transitions can be seen in table **9**. The effect of wealth on a transition from healthy to unhealthy is insignificant, therefore we can conclude that the wealth of the base year does not have an effect on the chance of transitioning from healthy to unhealthy. This implies that there is not a causal effect from wealth to health. Education is significant in the 2007 – 2013 regression (p < 10%) and the 2013-2017 regression (p < 1 %). The coefficients mean that a highly educated person has a 6.7 percentage point between 2007 - 2013 and 3.2 percentage point between 2013-2017 lower chance to decrease in health scale. The gender coefficient is significant (p < 10%) in the 2007 – 2013 regression which tells us that in that period a male had a 7.3 percentage point higher chance of decreasing in health scale than a woman The results found here contradict the findings of Cai (2009) as she did find a significant effect from wealth on the transition chance.

Table 10: Health transition results

|  |  |  |
| --- | --- | --- |
|  |  |  |
|  | 2007-2013 | 2013-2017 |
| VARIABLES | transitioned | transitioned |
|  |  |  |
| net wealth | 0.0000 | 0.0000 |
|  | (0.0000) | (0.0000) |
| education | -0.0674\* | -0.0322\*\*\* |
|  | (0.0363) | (0.0121) |
| gender | 0.0727\* | -0.0068 |
|  | (0.0405) | (0.0129) |
| unemployed | -0.0522 | -0.0140 |
|  | (0.0950) | (0.0395) |
| net income | -0.0000 | -0.0000 |
|  | (0.0000) | (0.0000) |
| Constant | 0.2144\*\*\* | 0.0411\*\*\* |
|  | (0.0337) | (0.0115) |
|  |  |  |
| Observations | 513 | 588 |
| R-squared | 0.0190 | 0.0175 |
| Standard errors in parentheses | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | |  |

# Robustness tests

To test whether the results are valid, several robustness tests have been run. First there is a pretreatment tests to test that the health of the control and treatment group behaved in the same way before the treatment, i.e. to test whether the parallel trend assumption of the difference in difference analysis is likely to hold. Secondly, two tests were run to check whether the treatment had the desired effect. The first tested if the net wealth of people with a house reacted in a significantly different way to the change in housing prices than the net wealth of people who rented a house. The second test tested if the treatment did also affect the net income of the control and treatment group in a different way which should not be the case. Thirdly, tests have been run to see whether or not the characteristics of the group with all observations have changed between before and after the treatment. This is important to tell whether the effects found in the DID analysis of the all-observations group is solely accountable to the wealth difference caused by the treatment or that changes in characteristics may also have played a part.

The way the average health behaves can be visually inspected. Figure 2 shows the fitted lines of average health throughout the years 1995 to 2006. One assumption of the difference in differences analysis is that the average health of the control and treatment group behave exactly the same. We can never know if it is the case during the treatment period but at least we could check if the lines are parallel in the pretreatment period. (the parallel lines assumption). If this is the case this gives us some confidence that the assumption is met in the treatment period. Otherwise there will be a difference in the differences by simply dividing the observations in different groups. In figure 2 it can be seen that the lines are not perfectly parallel. They do however act in the same way, they are both descending but worryingly the differences are increasing over time. To test the severity of the violation of the assumption, an DD analysis with a placebo intervention with 2001 as the pretreatment period and 2006 as the posttreatment period is run to see if the health of both groups differ significantly.

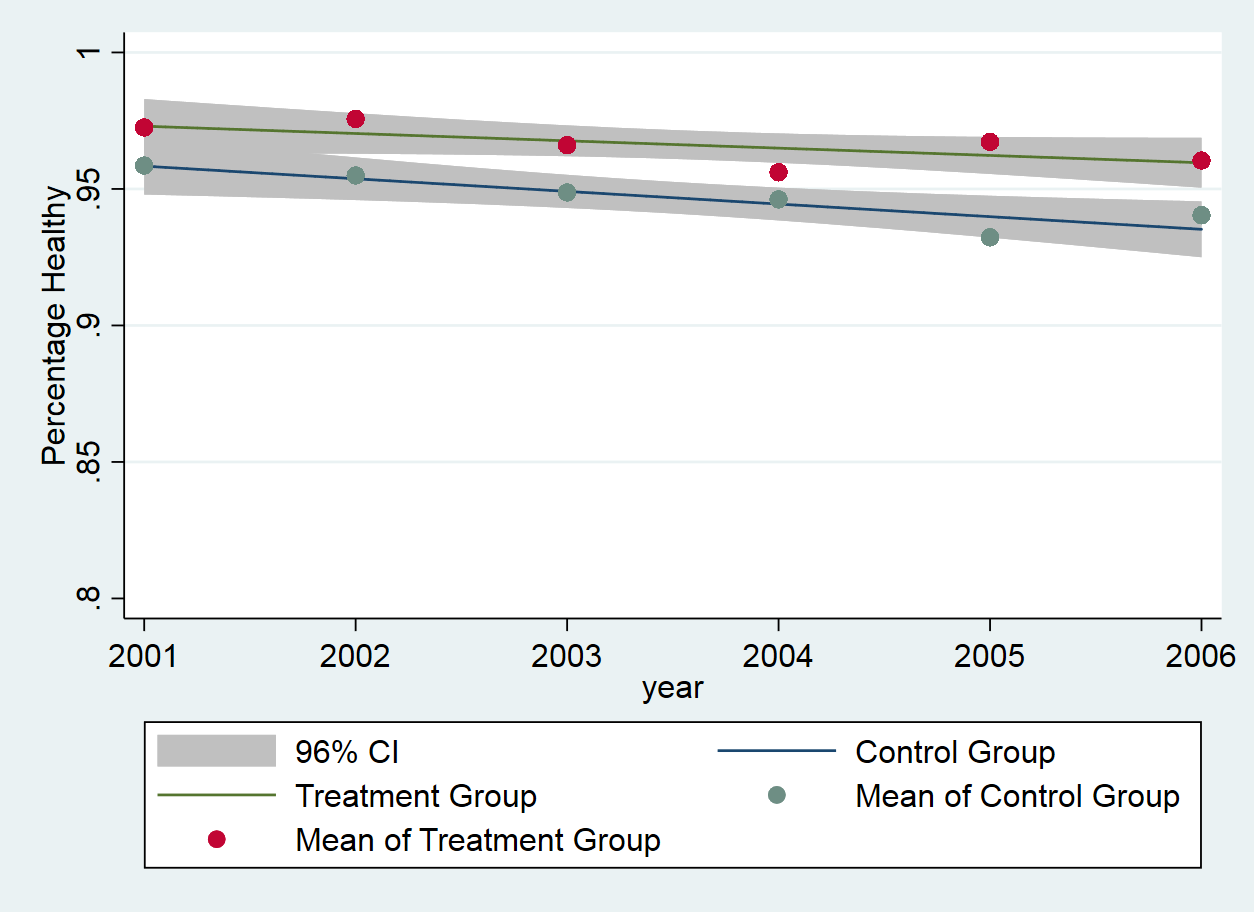


Figure 2: fitted lines through the average health of the control and treatment group

The results of the DD analysis with the placebo intervention can be seen in table 9. Here the pretreatment and posttreatment years are respectively 2001 and 2006. The DID coefficient is insignificant which implies that although the lines do not behave in exactly the same way, they do not produce a significant difference. Therefore, even though the parallel lines assumption is not perfectly met, the results are still useable but not as robust as possible.

Table 11: Placebo intervention

|  |  |
| --- | --- |
|  |  |
|  | 2001 - 2006 |
| VARIABLES | Health |
|  |  |
| DID | 0.0061 |
|  | (0.0138) |
| time | -0.0182\*\* |
|  | (0.0090) |
| treated | 0.0139 |
|  | (0.0102) |
| Constant | 0.9586\*\*\* |
|  | (0.0064) |
|  |  |
| Observations | 3,610 |
| R-squared | 0.0030 |
| Standard errors in parentheses | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | |
|  | |

## Mechanism tests

In order to see if the financial crisis only affected wealth in a different way in the control and treatment group, two mechanism tests were conducted. One on the effect of the treatment on wealth and one on income.

The results of the mechanism test on net wealth can be seen in table 10. This test tests whether or not the mechanism had the desired effect on the net wealth. This was also done using a DD analysis but this time with the net worth of a person as the dependent variable. If the financial crisis and the bounce-back had the expected effect on the net worth of both the groups, i.e. more an effect on the net worth of the home owners than the tenants, the DID coefficient should be significant. Also, the DID coefficient should then be negative in the 2007-2013 regression and positive in the 2013-2017 regression.

As can been seen in table 11, in the sample where this study only uses recurring individuals, the DID coefficient is significant in the 2007 – 2013 regression without fixed effects and in both the regressions with fixed effects. Since the fixed effects should only increase the accuracy of the estimates, it can be concluded that in the same persons group the treatment did have the desired effect on the net wealth on home owners and home renters. The fact that the fixed effects regression increases accuracy can be seen in the fact that the coefficients remain roughly the same while the standard deviations decrease substantially. The significant DID coefficients show that because of the treatment, the change in housing prices, the net wealth of a person in the treatment group, a home owner, changed more than the net wealth of an individual in the control group, a renter. Therefore, a different change in health between the two groups is likely to be caused by the treatment since other characteristics do not matter too much in the fixed effects regression.

In the all-observations sample, the DID coefficient is not significant in both periods. this implies that in the all-observations group the treatment did not have the desired effect, i.e., the net wealth of people in the treatment group did not change in a significantly different way than the net wealth of the people in the control group. The coefficients are however correct in them being respectively negative and positive. Since the treatment did not have the desired effect, the results of the all-observations group do not tell us whether wealth does or does not have a significant effect on health. This could possibly be caused by individuals buying or selling a house during the treatment period and therefore moving between the control and treatment period.

Table 12: mechanism check

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | All observations | | | | same persons | | | | | Same persons with fixed effects | |
|  | | 2007 - 2013 | | 2013 - 2017 | | 2007 - 2013 | | 2013 - 2017 | | | 2007-2013 | 2013-2017 |
| VARIABLES | | netWorth | | netWorth | | netWorth | | netWorth | | | netWorth | netWorth |
|  | |  | |  | |  | |  | | |  |  |
| DID | | -22,284.3976 | | 3,935.3058 | | -43,859.3439\*\* | | 24,568.2392 | | | -43,859\*\*\* | 24,568\*\*\* |
|  | | (14,351.1254) | | (13,527.6009) | | (22,173.0856) | | (20,922.0809) | | | (16,266) | (9,173) |
| time | | 3,533.7450 | | 2,597.1789 | | 3,590.2866 | | 4,134.4751 | | | 3,590 | 4,134 |
|  | | (9,902.1682) | | (9,605.9329) | | (16,172.7649) | | (15,970.2638) | | | (11,864) | (7,002) |
| treated | | 249,872.3663\*\*\* | | 227,587.9687\*\*\* | | 270,696.3636\*\*\* | | 252,832.5642\*\*\* | | | - | - |
|  | | (9,924.4048) | | (10,237.9793) | | (15,678.7392) | | (14,794.1452) | | |  |  |
| Constant | | 25,399.5137\*\*\* | | 28,933.2587\*\*\* | | 24,633.7423\*\* | | 30,166.8933\*\*\* | | | 168,646\*\*\* | 177,482\*\*\* |
|  | | (6,742.6159) | | (7,162.1051) | | (11,435.8717) | | (11,292.6818) | | | (5,739) | (3,199) |
|  | |  | |  | |  | |  | | |  |  |
| Observations | | 3,458 | | 3,864 | | 1,406 | | 1,730 | | | 1,406 | 1,730 |
| persons | |  | |  | | 0.2670 | | 0.2726 | | | 703 | 865 |
| R-squared | | 0.2442 | | 0.2346 | | 0.2619 | | 0.2628 | | | 0.0185 | 0.0268 |
| Standard errors in parentheses | | | | | |  | |  | | |  |  |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | |  | |  | |  | | |  |  |
|  | |  | |  | |  | |  |

The results of the mechanism test on income can be seen in **TABLE 12!!!@#!@**. The DID coefficients are insignificant in all regressions which implies that the difference in income of the treatment and control group did not change significantly. This implies that the treatment did not have an undesired effect on income which could have influenced health through the income channel.

Table 13:mechanism test income

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | same observations | | recurring individuals | | | recurring individuals fixed effects | | |
|  | 2007 - 2013 | 2013 - 2017 | 2007 - 2013 | 2013 - 2017 | | 2007-2013 | | 2013-2017 |
| VARIABLES | net income | net income | net income | net income | | net income | | net income |
|  |  |  |  |  | |  | |  |
| DID | -1,028.4244 | 1,431.8299 | -941 | -472 | | -940.9913 | | -472.1626 |
|  | (1,065.0406) | (1,193.3185) | (1,779) | (1,938) | | (1,191.1214) | | (1,447.9558) |
| time | 2,964.3806\*\*\* | -31.3424 | 1,499 | 1,972 | | 1,498.5655\* | | 1,971.7267\* |
|  | (752.7164) | (872.0241) | (1,346) | (1,541) | | (901.1107) | | (1,151.2502) |
| treated | 14,764.5710\*\*\* | 13,736.1466\*\*\* | 16,481\*\*\* | 15,152\*\*\* | | - | | - |
|  | (721.9053) | (885.6953) | (1,258) | (1,370) | |  | |  |
| Constant | 13,641.0400\*\*\* | 16,605.4207\*\*\* | 14,081\*\*\* | 16,259\*\*\* | | 23,513.5160\*\*\* | | 25,836.9049\*\*\* |
|  | (505.3264) | (631.0079) | (952) | (1,089) | | (416.6957) | | (493.7222) |
|  |  |  |  |  | |  | |  |
| persons |  |  |  |  | | 477 | | 541 |
| Observations | 2,586 | 2,671 | 954 | 1,082 | | 954 | | 1,082 |
| R-squared | 0.2255 | 0.1855 | 0.2552 | 0.1823 | | 0.0069 | | 0.0107 |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | |  |  | |  | |

## Characteristics

The results of the tests testing whether the characteristics have changed in the “all observations group” can be seen in table 11. Table 11 shows respectively the changes in gender, education and net income. One of the assumptions is that because the treatment should only affect the difference between the control and treatment group, i.e. owning a house or not in this case, the other differences should cancel out before and after the treatment. For this assumption to hold, the DID coefficients need to be insignificant because otherwise health might be explained partly by one or more of the changed characteristics. Because characteristics have remained the same in the group with only observations of repeated repliers, this could only form a problem in the all observations group.

Table 11 shows that there is a significant difference in differences in gender between the control and treatment group in 2013-2017 (p<10%). Between 2013 and 2017 the percentage of females in the treatment group dropped by 6.4 percentage points more than in the control group. This implies that the effects measured in 2013 – 2017 regressions on health could be explained by gender instead of wealth as was the idea. The other three tested characteristics, education, net income and unemployment, did not significantly change. So the only characteristic that changed significantly is gender in the period of 2013 – 2017. Therefore, some of the variation of the difference in health in the period 2013 – 2017 between the control group and treatment group might be explained by the change in the male to female ratio.

Table 14: characteristics check

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | 2007 - 2013 | | | 2013 -2017 | | 2007-2013 | 2013-2017 | 2007-2013 | 2013- 2017 | |
| VARIABLES | | | gender | | | Gender | | education | education | net income | net income | |
|  | | |  | | |  | |  |  |  |  | |
| DID | | | -0.0052 | | | -0.0644\* | | -0.0392 | 0.0111 | -1,028 | 1,431 | |
|  | | | (-0.036) | | | (-0.0362) | | (-0.038) | (-0.0379) | (-1,065) | (-1,193) | |
| time | | | 0.0133 | | | -0.0008 | | 0.0807\*\*\* | -0.0678\*\* | 2,964\*\*\* | -31.3424 | |
|  | | | (-0.0254) | | | (-0.0265) | | (-0.0268) | (-0.0277) | (-752) | (-872) | |
| treated |  | | 0.3971\*\*\* | |  | 0.3919\*\*\* | | 0.2010\*\*\* | 0.1619\*\*\* | 14,764\*\*\* | 13,736\*\*\* |
|  |  | | (-0.0244) | |  | (-0.0269) | | (-0.0257) | (-0.0281) | (-721) | (-885) |
| Constant | | | 0.3576\*\*\* | | | 0.3709\*\*\* | | 0.2749\*\*\* | 0.3556\*\*\* | 13,641\*\*\* | 16,605\*\*\* | |
|  | | | (-0.0171) | | | (-0.0192) | | (-0.018) | (-0.02) | (-505) | (-631) | |
|  | | |  | | |  | |  |  |  |  | |
| Observations | | | 2,586 | | | 2,671 | | 2,586 | 2,671 | 2,586 | 2,671 | |
| R-squared | | | 0.1584 | | | 0.129 | | 0.0395 | 0.0317 | 0.2255 | 0.1855 | |
| Standard errors in parentheses | | | | | |  | |  |  |  |  | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | | | | | |  | |  |  |  |  | |
|  | | |  | |  | | |

Table 15 characteristics continued

|  |  |  |
| --- | --- | --- |
|  | 2007 - 2013 | 2013 - 2017 |
| VARIABLES | unemployed | unemployed |
|  |  |  |
| DID | 0.0033 | -0.0102 |
|  | (0.0114) | (0.0126) |
| treated | -0.0009 | 0.0024 |
|  | (0.0077) | (0.0093) |
| time | 0.0150\* | -0.0011 |
|  | (0.0080) | (0.0092) |
| Constant | 0.0140\*\*\* | 0.0291\*\*\* |
|  | (0.0054) | (0.0067) |
|  |  |  |
| Observations | 2,586 | 2,671 |
| R-squared | 0.0034 | 0.0008 |
| Standard errors in parentheses | | |
| \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 | |  |

**Conclusion**

This paper uses a difference in differences analysis and an analysis on health transitions to try and find a causal relationship from wealth to health in the Netherlands. The treatment in the difference in differences analysis was the change in housing prices caused by the financial crisis and the subsequent bounce back of the housing prices. The DID analysis was done on two samples, one with all observations available and one that only consisted of repeated observed individuals. The transitions this study used were negative transitions where a person transitioned from a higher to a lower health scale. Wealth is defined as the net worth of a person.

The DID analysis showed no causal effect from wealth on health in the recurring observations sample. The results from the all observations sample are not robust as the mechanism in this sample did not have the desired effect. The analysis on health transitions rather than health status also showed no causal effect from wealth on health which corresponds to the findings of the DID analysis.

Therefore it can be concluded that there is no evidence of a causal effect which runs from wealth to health in the Netherlands in the short term.

`

**Discussion**

As was pointed out in the introduction, the relationship between wealth and health has three possible directions, wealth could affect health, health could affect wealth and another factor could affect health and wealth in the same direction. As was pointed out in the constitutional section, the effect from health to wealth is not likely to hold in the Netherlands. Since this paper found evidence that the effect from wealth to health is also insignificant, the third option, another factor that affects health and wealth in the same way seems the most likely in the Netherlands. Research should be done to confirm if this is the case.

There are some factors that might have influence on the results of this paper that were out of the scope of the paper to control for. Firstly, the sample used was rather small, especially in the same persons sample in the DID analysis and the sample for the health transitions. This might have increased the error and made the estimates less accurate. Research that uses a bigger sample might find different results.

Secondly, other factors might have impacted health of the control and treatment group differently between the pre- and posttreatment years. One thing that might have had this effect is the lowering of the mortgage interest deduction between 2013 and 2017 (HomeFinance BV, n.d.) . This may have the income of the of the treatment group and not the control group because the treatment group owns a house and is therefore more likely to have a mortgage. The lowering of the mortgage interest deduction caused a lower net income of the individuals who had a mortgage since they received a lower deduction from the income tax they had to pay. The lower income could have caused a worse health, therefore reducing the estimated effect of wealth on health in the 2013 – 2017 analysis. However, as can be seen in table <><>!@#!@DE INCOME MECHANISM CHECK<><!@#!@ we found no evidence that income between the control and treatment group changed in a significant different way between the two groups.

Another reason why this study might not have found any significant results is that the average health found in the sample is nearly perfect. This means that improvements in health are very hard to accomplish. This implies that especially in the DID analysis of 2013 – 2017, were an increase in health was expected since the housing prices rose, it is very hard to find significant improvements in health. It would be interesting to see if different results are found if the DID method used in this paper was conducted in a country with a lower average health.

This paper contributed to the current literature in showing that there is no evidence of a causal effect of wealth on health in the Netherlands. This also means that public policy to increase the average health of the Netherlands should not focus on increasing the wealth of individuals.

**Literatuur**

Aittomäki, Martikainen, Laaksonen, Lahelma, & Rahkonen. (2010). The associations of household wealth and income with self-rated health – A study on economic advantage in middle-aged Finnish men and women. Social Science & Medicine, 71(5), 1018-1026.

Apouey, B., & Clark, A. (2015). Winning Big but Feeling no Better? The Effect of Lottery Prizes on Physical and Mental Health. Health Economics, 24(5), 516-538.

Au, N., & Johnston, D. (2015). Too Much of a Good Thing? Exploring the Impact of Wealth on Weight. Health Economics, 24(11), 1403-1421.

Belastingdienst. (2018, December 06). Hoogte van mijn inkomen. Retrieved January 29, 2019, from https://www.belastingdienst.nl/wps/wcm/connect/bldcontentnl/belastingdienst/prive/toeslagen/zorgtoeslag/voorwaarden/inkomen/

Cai, L. (2009). Be wealthy to stay healthy: An analysis of older Australians using the HILDA survey. Journal of Sociology, 45(1), 55-70.

CBS. (2019). CBS Statline. Geraadpleegd op 23 januari 2019, van https://opendata.cbs.nl/statline/

CentERdata. (2019). DHS data access. Retrieved January 2, 2019, from <https://www.dhsdata.nl/site/users/login>

CentERdata. (n.d.). DHS data access | CentERdata.nl. Retrieved January 2, 2019, from <https://www.centerdata.nl/en/databank/dhs-data-access>

Het Juridisch Loket. (n.d.). Krijg ik loon doorbetaald bij ziekte? | Het Juridisch Loket. Retrieved January 15, 2019, from <https://www.juridischloket.nl/werk-en-inkomen/ziekte-en-zwangerschap/loondoorbetaling-bij-ziekte/#Ik-heb-een-tijdelijk-contract>

HomeFinance BV. (n.d.). Verdere beperking hypotheekrenteaftrek door nieuw kabinet. Retrieved January 23, 2019, from <https://www.homefinance.nl/nieuws-blog/blogberichten/9318/verdere-beperking-hypotheekrenteaftrek/>

Hurd, M., & Kapteyn, A. (2005). Health, wealth, and the role of institutions. In *Multidisciplinary Economics* (pp. 307-332). Springer, Boston, MA.

Idler, E., & Benyamini, Y. (1997). Self-Rated Health and Mortality: A Review of Twenty-Seven Community Studies. Journal of Health and Social Behavior, 38(1), 21-37.

Keese, M., & Schmitz, H. (2014). Broke, Ill, and Obese: Is There an Effect of Household Debt on Health? Review of Income and Wealth, 60(3), 525-541.

Kim, B., & Ruhm, C. (2012). Inheritances, health and death. Health Economics, 21(2), 127-144.

Meer, Miller, & Rosen. (2003). Exploring the health–wealth nexus. Journal of Health Economics, 22(5), 713-730.

Michaud, & Van Soest. (2008). Health and wealth of elderly couples: Causality tests using dynamic panel data models. Journal of Health Economics, 27(5), 1312-1325.

Pollack, Chideya, Cubbin, Williams, Dekker, & Braveman. (2007). Should Health Studies Measure Wealth?: A Systematic Review. American Journal of Preventive Medicine, 33(3), 250-264.

UWV. (n.d.). Mijn werknemer is ziek: loon doorbetalen | UWV | Werkgevers. Retrieved January 15, 2019, from https://www.uwv.nl/werkgevers/werknemer-is-ziek/loondoorbetaling/werknemer-is-ziek-loon-doorbetalen/detail/loon-doorbetalen-tijdens-ziekte

Zilveren Kruis. (2019). Eigen risico. Wat is het en waarom betaalt u het? - Zilveren Kruis. Retrieved January 15, 2019, from https://www.zilverenkruis.nl/Consumenten/zorgverzekering/basisverzekering/Paginas/eigen-risico.aspx