The impact of a household income shock on the consumption of healthcare in the Netherlands.

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05-08-2021

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Wordcount: 9906

Abstract

With the introduction of a cost-sharing mechanism, we could argue that income and liquidity issues play a role in individual healthcare consumption. Yet the current research is not conclusive about the role of income on healthcare consumption. This study attempts to shed light on the effect of a large income drop and its effect on healthcare expenditure in the Netherlands. With panel data and a difference-in-differences analysis we study the effect of an income drop at household level on individual healthcare expenditure. The results of our study suggests that individual healthcare expenditure is affected by a drop in income and that mainly general practitioner- and mental care are affected. However, changes in the basic health insurance plan seem to interfere with our results.

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1. INTRODUCTION

Many economists argue that health insurances need to have some form of cost-sharing mechanism (Gross et. al., 2020). The idea behind a cost-sharing mechanism is that when a part of the healthcare costs is shared with the insured, it will incentivize the insured to make a cost benefit analysis (Remmerswaal & Boone, 2020). This can make the insured more price sensitive (Remmerswaal & Boone, 2020). One could also argue that by introducing a cost-sharing mechanism, income will play a role again in the access and usage of healthcare services. A low-income individual might face financial constraints in consuming care by the increased price of care.

It could thus be argued that income may play a role in the decision making to consume healthcare in a cost-sharing model. Across OECD countries patients pay on average one fifth of the healthcare costs out-of-pocket. Household spending on pharmaceutical and medical goods is the main healthcare expenses followed by outpatient care, both accounting for two-thirds of household spending on healthcare (OECD Indicators, 2019). Yet, current research is not conclusive about the role of income on healthcare consumption (Baicker & Goldman, 2011). Some research finds an effect between income and healthcare consumption under a cost-sharing model (Manning et al. 1987; Beck, 1974; Gross et al., 2020) and other research finds no impact at all (Gross & Tobacman, 2014; Cherkin et al., 1989). As far as we know, nothing is known about the effect of an income change on healthcare consumption.

In this thesis we attempt to shed light on the effect of a large income drop on healthcare expenditure in a mandatory deductible scheme. We do this research in an attempt to understand if individuals change their healthcare consumption when faced with a change their budget. To research this we look at the effect of a large income drop at household level on individual healthcare expenditures in the Netherlands. We compare healthcare expenditures of individuals who experience a large income drop at household level to individuals who have a stable household income by using a difference-in-differences analysis. As far as we know, we are the first to study the effect of a large income dop at household level on healthcare expenditure. In this thesis we first look at the effect of an income drop on the total healthcare expenditure. To understand which type of care is mostly impacted, we also analyze the effect on different types of care. Lastly, we look at how sub-groups (based on gender, age, income categories and ethnicity) respond differently on a large income shock. In this study we hypothesize that individuals who experience a large income shock consume less healthcare and that some care is affected more than others.

In our analysis we find that individuals who experience a large drop in their household income spend less on healthcare. The effect gets stronger over time and mainly general practitioners (GP) care and mental care are affected. Men and individuals with a low income respond the strongest to an income drop. The results suggest that there is an effect of an income drop at household level on individual healthcare expenditure. However, changes in the basic health insurance plan over time seem to interfere with our results.

2. THEORETICAL BACKGROUND

Before we start the research, we need to make a distinction between three definitions that affect the purchasing behavior of a person: cost-benefit analysis, liquidity constraints and liquidity sensitivity. A cost-benefit analysis is the process used by a person to measure benefits of a decision or action minus the costs of taking that action (Cambridge business English dictionary, 2011). This analysis helps a person to make a decide to act or not. A cost-benefit analysis is income dependent and is therefore sensitive to income changes. Liquidity constraints is the absents of financial means that affect the ability of a person to purchase a good or service (Williamson, 2018). Liquidity constraints can also affect the cost-benefit analysis of a person in the decision-making process to purchase healthcare services over another good or service. While low-income individuals have a higher change to be liquidity constrained than others, they are not constrained by definition. Liquidity sensitivity is the phenomenon where individuals delay purchases until their income arrives (Gross et al., 2020). Liquidity sensitivity can also affect a person's cost-benefit analysis. In this thesis we sometimes refer to both liquidity constraints and liquidity sensitivity by using the term liquidity issues.

To form our hypothesis, we look at the empirical evidence and the existing literature on the effect of income on healthcare expenditure. We look in this section at the effect of income in a cost-sharing model; the effect of income on the use of different types of care and the empirical evidence on liquidity issues in healthcare consumption.

2. 1 Cost-sharing and income

A large amount of research has found that in general individuals are price sensitive regarding healthcare consumption (Zweifel & Manning, 2000). The most well-known research is the RAND experiment, that demonstrated with a price elasticity of -0.2, that price does affect medical utilization (Manning et al., 1987).

However, when looking at the effect of income (instead of price) on healthcare consumption, the literature is less conclusive. The RAND experiment itself shows different outcomes. The researchers found that within each insurance family plan the probability of use of any medical service increased with income. Also, in the individual plans there was a 10 percent increase in medical expenses between the bottom and the top third of the income distribution, yet this difference was insignificant (Manning et al., 1987). Other research found a small positive and statistically significant relationship between income and use of medical services. Research of Beck (1974) for example found an income elasticity of 0.03. Most other research also found a small and often neglectable income elasticity below 1.0 (Freeman, 2012; Manning et al., 1987; Newhouse & Phelps, 1976). This low effect of income is consistent with the hypothesis that an insurance (partially) removes the income barriers to healthcare services (Beck, 1974).

Some other studies find no effect of income on healthcare use within a co-payment system (Zweifel & Manning, 2000). As mentioned above the RAND experiment did not find a statistically significant difference in the individual plans (Manning et al., 1987). Another study on the effect of copayments ($5 for outpatient services and $25 for emergency room visits) by Cherkin et al. (1989) found also no difference in response by income.

2.2 Types of care

If income plays a role on healthcare consumption in a cost-sharing scheme, then it is also important to understand if high or low valuable care is impacted. A cost-sharing scheme can be welfare enhancing if spending is reduced on low value care. If patients, on the contrary, reduce spending on high value care then a cost-sharing scheme can be harmful (Hayen et al., 2018). From the literature we know that insured individuals as a response to cost-sharing mechanism lower quantity of care used by cutting costs all over the healthcare spectrum (Brot-Goldberg et al., 2017). But when we look at the effect separate by income-groups, we see a different effect.

We see that low-income groups cut costs differently along the healthcare spectrum than other income groups (Cameron, 1988). Beck (1974) shows that while costs are cut over the healthcare spectrum after the introduction of a co-payment mechanism[1], the decline is the highest among poor households in patient-elective[2] services and specifically in GP visits. He found a higher drop of GP services among the poor (18%) than the overall mean of 6 percent after the introduction of a co-payment system. While of a smaller impact and with no statistically significance, he also found a reduction of specialist services among the poor under a co-payment system (Beck, 1974). Beck noticed in his research that mainly patient-elective care is affected because patients themselves can choose

[1] Co-payment (in Canadian dollars) of $1,50 per doctor visit and $2 per home visit.
[2] Patient-elective care in the paper of Beck (1974) is described as care patients can use without the need of a prescription.

to use this type of care or not. The decline could be a result from forgoing overutilization, but this was not confirmed in the study (Beck, 1974).

Furthermore, low-income individuals (more often than high-income individuals) delay or forgo high value health care (Kullgren et.al., 2010). In a study by Wharam (2019) among women and breast cancer screening, they found through a pairing system a delay in screening among low-income women with a high deductible. Low-income women in health insurance plans with a high deductible waited 1,6 months longer for diagnostic breast imaging and 2,7 months longer for breast biopsy compared to low-income women with a low deductible. Among these women, the time to incident early-stage breast cancer diagnosis was 6,6 months longer and time to first chemotherapy was 8,7 months longer under a high deductible plan. However, these differences found were not statistically significant (Wharam, 2019). While this research did not examen the reason behind the delay, a possible argument could be that the low-income women with a high deductible first had to save money to face the high-out-of-pocket expenditure (liquidity sensitivity). Chandra et. al. (2021) also found that a small increase in cost-sharing causes patients to cut back on drugs with large benefits. Because low-income individuals also report more often difficulties with understanding their health insurance plans, it might be that they are more likely to question the value of services requiring out-of-pocket expenditures, and that they therefore more easily forgo care (Kullgren et al., 2010).

2.3 Liquidity constraints and sensitivity

A reason for individual to forgo care under a cost-sharing model are liquidity issues. When looking at consumption in general, a large literature body suggests that many low-income households wait to consume until their income arrives (Olafsson & Pagel, 2018). This liquidity sensitivity, can be problematic when it comes to healthcare consumption. Medical necessity should ideally determine the purchase of a treatment, not the arrival of income (Gross et al., 2020). It also should be taken into account that liquidity constraints are hard to measure and that other factors than liquidity constraints or liquidity sensitivity (like: poor financial planning or priority shifts) can play a role in the decrease of consumption.

One empirical research of Gross et al (2020) on liquidity constraints measured an increase in prescription fill of 10 to 12 percent among low-income recipients receiving subsidized copayments on paydays. These effects seem to diminish when recipients' copayments are reduced, indicating that liquidity constraints among low-income individuals exists (Gross et.al., 2020). As an explanation the authors states that liquidity sensitivity might be due to behavioral frictions making it psychologically difficult to expend resources when cash is scarce (Gross et al., 2020).

Patients themselves indicate that they forgo care due to (potential) costs that are related to medical service (Kullgren et.al., 2010) which could also point towards liquidity issues. So indicated a third of the Americans that they "skipped filling a prescription due to its costs" which is an effect not only measured by the uninsured (Goetz, 2018). Respondents from a low-income family and high deductible health plans indicated that they would be likely to ask their physician about delaying services that are not covered (Kullgren, et. al., 2010). Financial stress attributable to medical bills instead of supply shortages seems to form a barrier to needed and recommended care for low-income adults (Blendon et al., 20002).

2.4 Hypothesis

Based on the literature discussed above, we hypnotize the following for our research. We expect that individuals who experience an income drop will lower their healthcare expenditures compared to individuals who maintain a stable household income. Furthermore, we expect that some care is affected more than others. In this research we expect to see the biggest impact on GP care, as the GP is for many patients the first entry point into the healthcare system.

3. INSTITUTIONAL SETTING

In 2006 the Dutch government introduced the Dutch Healthcare Act ("Zorgverzekeringswet"). This act obliged each individual in the Netherlands to buy a basic, nationally standardized, insurance plan from a private health insurer (Van de Ven & Schut, 2008). The basic health insurance plan is the same for everyone and the insurance plan is determined by the government (Remmerswaal et. al., 2019). The insured can also opt for supplementary insurance to cover healthcare that is not included in the basic coverage package and the insured is not obliged to buy supplementary insurance from the same insurer as for their basic coverage package (Hayen et. al., 2018).

From 2008 onward, each health insurance contract is required to include an annual deductible. Under the mandatory deductible scheme all individuals aged 18 years and older pay out-of-pocket for healthcare services up to the deductible limit (Hayen et.al., 2018). It is the government that decides the limit of the deductible. In 2008 the deductible was 150 euro and this gradually increased each year and is in 2021 at a height of 385 euro. This means that in 2021 an individual pays for care in the basic health insurance plan a maximum of 385 euro (excluding opportunity costs) (Remmerswaal & Boone, 2020). The deductible applies for nearly all services, yet some services like GP and maternal care are exempted (Remmerswaal et. al., 2019). On top of the mandatory deductible an individual can also opt for a voluntary deductible of a maximum of 500 euro in exchange for a lower insurance premium**.** The premiums are community-rated so that the insurance premium is the same across patients, irrespective of their individual characteristics (Hayen et. al, 2018).

To avoid that low-income groups are hindered by the deductible to access healthcare, several compensation arrangements exist. Low-income groups can receive a monthly income dependent subsidy to pay for their insurance premium and healthcare costs. Insureds receive this payment on their own bank account and are themselves responsible to use the subsidy to pay their premium or deductible. Reinsurance of the mandatory deductible through the municipality is possible for people with a low income. In 2020 around 683.000 individuals had this reinsurance (Dutch Healthcare Authority, 2020). Municipal financial support for people on social welfare is available as also the option to deduct high healthcare costs from taxes (Esch et al, 2018). Each of these schemes requires that the insured themselves has to apply by the right institution to receive these subsidies and financial support. This requires from the insured to be aware of the regulations and know where they can go to make their application (Esch et al., 2018). While these compensation mechanisms exist, it does not automatically mean that each liquidity constrained individual receives financial support (due to a lack of knowledge that subsidies exist) or that they use the support to consume healthcare.

4. Data

For this thesis we use data from Statistics Netherlands (CBS). This is a Dutch government office that collects statistical data about the Netherlands. The data that we use is linkable data at the level of individuals and is not publicly available. We use datasets containing information about household incomes, healthcare costs, voluntary deductible and demographics information. All datasets cover a time span from 2011 to 2018. These datasets are separate sets that we have to clean and merge into one set that we can use for our analysis.

We start with a dataset that contains information about the individual income. For our analysis we use the variable yearly gross household income. We choose this variable because it gives a more holistic view on the financial situation of a person. Individuals might live in a family context or other household constructions with different income sources. A drop in one person's personal income might not impact the household budget drastically. Therefore, using the household income for our analysis provides us a more accurate image on the impact of an income drop. We clean our dataset by removing missing values and administrative errors. More details about the data cleaning process can be found in the appendix in chapter 11 A.

The next step is to clean the dataset that includes the yearly healthcare costs and to merge this dataset with the income information. This dataset includes for each individual their total annual healthcare costs within the Dutch Healthcare Act (Zvw) for the basic health insurance plan. For the first analysis (chapter 6.2) we use the individual annual healthcare costs minus the GP registration fee. The GP registration fee is a fixed quarterly fee that the insurance pays (which does not influence the deductible) to a person's GP to cover administration costs (CBS, 2018). We do not want to include the GP registration fee as this cost is not linked to healthcare consumption. The total healthcare expenditures are in the dataset also broken down into different categories of care. When we analyze the different categories of care (chapter 6.3) we use GP care, mental care, hospital care, pharmacy and others[3]. Important to note here is that care like district nursing, sensory disability care etc. from the General Special Medical Expenses Act "Algemene Wet Bijzondere Ziektekosten" (AWBZ) moved to the Zvw basic health insurance plan in 2015 (Knopperts, 2020). In our dataset it is visible that those categories of care, only contain data starting from 2015. These variables are included in the variable total healthcare costs in the analysis in chapter 6.2, but we do not use them in the analyses of the sub-categories of care. The consequences of this change in the basic health insurance plan we discuss in chapter 6.3 and 8. Also change for mental healthcare happen within the Zvw in 2014. In 2014 onwards, all mental healthcare is included in the basic health insurance plan (Knopperts, 2020).

The other datasets we use are the sets that include information about the voluntary deductible and the individual demographic information. Regarding demographic information we only keep the

[3] The variable others contain healthcare costs for dental care, paramedic care, health tools, hospital transportation, antenatal care, care consumed abroad and the variable others of the dataset.

variables gender, year- and country of birth. With the variable year of birth, we calculate the age of each individual.

To do our analysis we create a baseline sample that excludes certain individuals. We exclude the persons who had a voluntary deductible at least once in our time period to rule out potential effects of the voluntary deductible, such as selection (Douven et al., 2016). We also exclude the 1 percent highest household incomes in the years before the shock as this includes the exceptionally rich households in the Netherlands. As the mandatory deductible formally starts in the month after an individual's 18th birthday, we focus in our analysis on individuals who were at least 19 years or older in the beginning or our analysis (2011). This to guarantee that the persons in our analysis face the deductible for the full year throughout the whole analysis.

To summarize, our sample includes individuals born after 1993 who never choose a voluntary deductible and who do not belong in the richest 1 percent of the population. In our dataset we have information about the individual gross yearly household income, their total annual healthcare costs and their demographic information such as gender, age and country of birth. The next step is to use our sample to create a treatment and control group.

5. METHODS

In this study we compare the healthcare expenditures before and after an income shock by comparing individuals who experience an income shock (treatment group) to individuals who do not experience an income shock (control group). We do this by using a difference-in-differences analysis. In this chapter we explain how we define the treatment and control group and explain the difference-in-differences regression equations we use.

5.1 Choice of treatment and control group

In the dataset we created (see chapter 4) we define a treatment and control group by using the variable yearly household income. By defining several criteria based on income we select the treatment and control group.

The first step is to define in which year an income shock has to take place for our treatment group. We select individuals in our treatment group who experience an income shock at household level in 2013. We do this to be able to measure a long-term effect of the income shock (5 years). Furthermore, 2013 is chosen because in the years after 2013 several changes within the basic health insurance plan happened in for example mental healthcare, district nursing etc. (CBS, 2018).

To create the treatment and control group we make a new variable in our dataset that calculates the percentage change per year in the gross household income. We plot this new variable in a distributional overview that shows us the mean, median, first and third quartile of the distribution, largest and smallest observation[4]. Based on this distribution we decide what percentage of negative change in the household income we use to define a large shock. We want the treatment group to have a stable income before and after 2013. This way we exclude individuals who recover directly from the income shock, which helps us to measure the long-term effect of an income shock. For the control group we want the individuals to have a stable household income in the years 2011 to 2018. The definition of a stable income we also define based on the same distributional overview.

In the distribution overview we observe that 10 percent of the sample had at least a 20 percent drop in their income[5] in 2013. Based on this distribution, we define the treatment group as individuals who experience a minimum of 20 percent income drop in the year 2013. A stable household income is

[4] Due to privacy reasons and to avoid revealing personal information we are not able to show the distributional overview.
[5] Due to privacy reasons and to avoid revealing personal information we are not able to give the exact income change of the 10th percentile.

defined between a range of 0 to 15 percent change in the gross household income in one year. Our treatment group therefore exists only of individuals who had a stable income before 2013, in 2013 experienced a drop in their income of at least 20 percent and after 2013 had a stable income again. The individuals in the control group do have an income change between 0 to 15 percent per year. In total we have 2.8 million individuals in our analysis. 2.593.064 individuals in the control group and 99.528 individuals in the treatment group.

When we plot the average yearly gross household income for the treatment and control group (as created above) over the years 2011 to 2018 in a graph, we get the results as shown in figure 1. In this figure you can observe that the average income of the control groups remains very constant over time. The average household in of the treatment group first lays above that of the control group, but drops below the average income of the control group after 2013. We discuss this further in chapter 6.1.

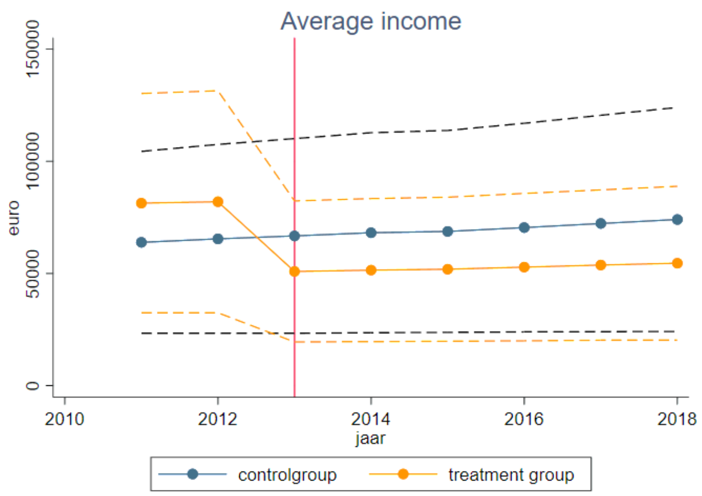

Figure 1: mean average household income of the control and treatment group including the standard deviation (dotted line) over the period of 2011 to 2018.

5.2 Parallel trend

For our analysis we use a difference-in-differences model. A critical assumption for the difference-in-differences analysis is that healthcare expenditure time trends for the control and treatment group are parallel before the income shock takes place (Wing et al., 2018). This must be tested for the treatment group in comparison with the control group. When the parallel trend assumption is tested and satisfied, the individuals without a household income shock serve as a valid counterfactual group of individuals who do experience a household income shock. To test the parallel trend assumption, we use the following estimation:

$$Y_{it} = c + Year_t + D_i + \beta_1 D_{2011} D_{treat} + \beta_3 D_{2013} D_{treat} + \beta_4 D_{2014} D_{treat} + \beta_5 D_{2015} D_{treat} + \beta_6 D_{2016} D_{treat} + \beta_7 D_{2017} D_{treat} + \beta_8 D_{2018} D_{treat} + e_{it} \quad (1)$$

Where Y_{it} expresses the individual healthcare costs of individual i in year t. c is the constant. $Year_t$ is a binary variable for year where we plot each year separately. We do not make this variable linear. D_{treat} is a binary variable where 1 identifies the treatment group and 0 the control group. D_{2011}, or indicated with any other year, is a year dummy which is 1 in the year indicated and 0 for the other years. To avoid multicollinearity, we remove the dummy variable for year 2012. D_i takes the fixed individual effect. e_{it} is the error term where we correct for non-observed effects. In our analysis we cluster our standard errors for persons as certain errors might be correlated across time and/or space. We estimate this equation and test if β_1 is zero and significant, then the parallel trends assumption holds. If β_1 is not significantly different from zero then both the treatment and control group do not have significantly different healthcare spending behaviors before the income shock takes place.

5.3 Difference-in-differences Model

As a first crude estimate of a treatment effect, we use a simple difference-in-differences calculation based on descriptive statistics. In this estimate we calculate first the average change in healthcare expenditure of the treatment and control group separately. Afterwards we subtract the difference in healthcare costs of the control group and the treatment group. This gives us a first idea of a treatment effect.

To estimate the treatment effect more precise, we use two different difference-in-differences models. The first model measures the average treatment effect where it compares the average difference between the control and treatment group in healthcare costs after the income shock. This first model looks as follows:

$Y_{it} = c + Year_t + D_i + \beta_1 D_{treat} D_{Post} + e_{it}$ (2)

Y_{it} are the individual annual healthcare costs of person i in year t. $Year_t$ is a binary variable for year where we plot each year separately. We do not make this variable linear. D_i takes the fixed individual effect. D_{treat} is a dummy variable for the treatment and control group which is 1 if an individual experienced a household income shock and 0 if no household income shock is experienced. This variable therefore determines if someone is in the control or treatment group. D_{Post} is a binary variable for treatment year 0 being before the year of the shock takes place and 1 after the income shock takes place. e_{it} is the error term where we correct for non-observed effects. $\beta_1 D_{treat} D_{Post}$ measures the average treatment effect comparing the healthcare expenditure differences between the treatment and control group after the income shock.

In the second model we estimate a more detailed treatment effect by using a model that looks at the post treatment yearly effect. This second model looks as follows:

$Y_{it} = c + Year_t + D_i + \beta_1 D_{2013} D_{treat} + \beta_2 D_{2014} D_{treat} + \beta_3 D_{2015} D_{treat} + \beta_4 D_{2016} D_{treat} +$
$\beta_5 D_{2017} D_{treat} + \beta_6 D_{2018} D_{treat} + e_{it}$ (3)

The outcome variable, the constant, the year, personal fixed effects remain the same. D_{2011} or indicated with any other year, is a year dummy which is 1 in the year indicated and 0 for the other years. D_{treat} remains also our treatment dummy. In this analysis we are interested in the coefficients of β_1 to β_6. These variables show per year the treatment effect comparing the treatment group to the control group.

6. RESULTS

6.1 Descriptive

Table 1 described our baseline sample and the composition of the treatment and control group. This table summarizes the average healthcare expenditure, yearly gross household income, age, gender and ethnicity before and after the shock in 2013. The control group contains 2,593,064 and the treatment group 99,528 unique observations (persons). We observe that the control and treatment group are before 2013 for most aspects comparable. Both groups have a similar average total healthcare cost with a little difference of 56.10 euro (difference of 2.2 percent). The control and treatment group have a slight difference in average age where the control group is older with 2.4 years (4.1 percent). Gender and ethnicity are distributed equally among the control and treatment groups. However, the two groups differ in the average income with a difference of 19,596 euro (35 percent) on average. After 2013 we see that for both groups the average total healthcare expenditure rose. The yearly gross household income for the treatment group is now lower than the that of the control group with an average of 10,871.63 euro (18.2 percent). On average the treatment group lost 26,845.34 euro (35.5 percent) of their yearly household income.

As indicated in chapter 5.3, we can make a first difference-in-differences estimation by calculating the difference between the total healthcare cost before and after 2013 for the control group compared to the two treatment groups. This calculation is demonstrated in table 2. Here we can see that with a difference of -174.61 euro, the treatment group spend less on healthcare than the control group after the income shock. This gives us a first indication that after a drop in the household income, individuals spend less on healthcare compared to individuals who do not experience a drop in their household income.

	2011-2012				*2013-2018*			
	Control (n=2.593.064)		Treatment (n=99.528)		Control		Treatment	
	Mean	Std. error	Mean	Std. error	Mean	Std. error	Mean	Std. error
Total healthcare costs (€)	2530.91	6731.99	2587.01	7405.08	3393.35	8636.19	3284.84	8659.99
Income (€)	56010.94	35872.81	75606.34	40043.96	59632.62	39879.97	48761.00	27824.72
Age (years)	57.93	16.26	55.55	15.29	61.93	16.34	59.55	15.38
Gender (frac.)	1.55	0.50	1.55	0.50	1.55	0.50	1.55	0.50
Nationality (frac.)	0.91	0.29	0.90	0.30	0.91	0.29	0.90	0.30

Table 1: descriptives of the treatment and control group before and after 2013 (the income shock). Male in the data is indicated in the dataset as 2 and female as 1.

	Healthcare costs before 2013	*Healthcare cost after 2013*	*Difference*
Control	€2530.91	€3393.35	€862.44
Treatment	€2587.01	€3284.84	€687.83
Difference-in-differences			- €174.61

Table 2: a simple difference-in-differences calculation based on the average healthcare costs before and after 2013 of the control and treatment group.

6.2 Total healthcare costs

For our analysis we look at the impact of an income shock on the total healthcare costs. Figure 2 gives a visual representation of total healthcare costs for the treatment and control group over the period of 2011 to 2018. In this figure we observe that the treatment group from 2013 onwards, has a less steep growth in their average healthcare costs compared to the control group. We also notice that the average healthcare costs of the treatment group shift from slightly above the control group to below the average of the control group form 2014 onwards.

While we calculated the first difference-in-differences estimate with the data from the descriptive statistics, we first have to do a parallel trend test. The results of this test are presented in table 3. Because β_1 (equation 1) is -37.88, but not significantly differently from 0, we can assume that the parallel trend holds.

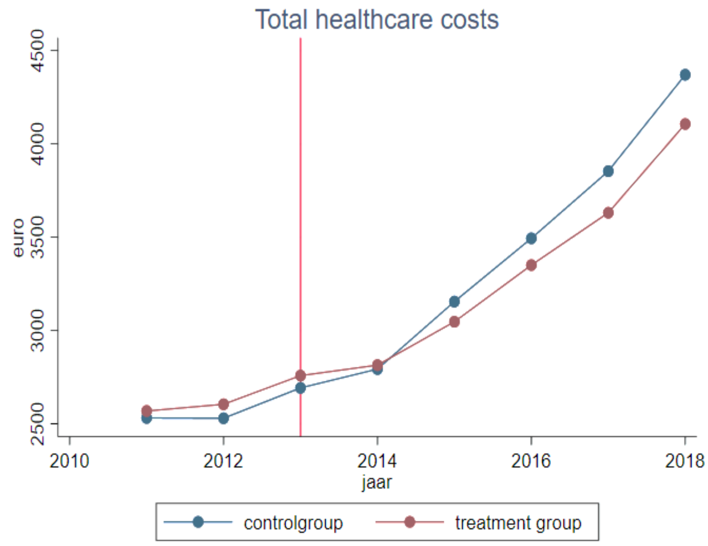

Figure 2: average yearly healthcare costs of the control and treatment group over the period from 2011 to 2018.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-37.88	28.67	0.187	-94.08 – 18.32
2013 (β3)	-9.28	28.49	0.745	-65.12 – 46.56
2014 (β4)	-53.62	29.44	0.069	-111.33 – 4.08
2015 (β5)	-183.15	31.39	0.000	-244.67 - -121.63
2016 (β6)	-218.38	32.82	0.000	-282.70 - -154.06
2017 (β7)	-297.93	34.24	0.000	-365.04 - -230.83
2018 (β8)	-338.97	38.88	0.000	-415.16 - -262.77

Table 3: the parallel trend test, based on equation 1 with outcome variable the yearly total healthcare costs.

In table 3 with the parallel trend estimate, we can already notice a pattern. We see that over time, the treatment group spends on average less on healthcare than the control group. We also see that the over time, the difference in healthcare costs between the treatment and control group increases to 338.97 euro in 2018. These results are in line with the pattern we observe in figure 2.

In table 4 we have the results of the first difference-in-differences estimate (equation 2) we measure that the average difference over time between the control and treatment group. We measure an average treatment effect of -164.61 euro, meaning that the treatment group after the income shock on average spends 164.61 euro less on healthcare than the control group. This average lays in a confidence interval between -207.16 and -122.07 euro and this result is statistically significant. This result differs from the first difference-in-differences calculations in table 2 because in this analysis we adjust for person fixed effects.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-164.61	21.71	0.000	-207.16 – -122.07

Table 4: the difference-in-differences analysis based on equation 2 estimating the average difference between the treatment and control group for the period after the income shock too place.

Table 5 contains the results of the second difference-in-differences estimation (equation 3) where we observe the treatment effects for every year after the shock separately. In this estimate we see that in the first two years after the large income shock the treatment group does not spend significantly different on healthcare than the control group. However, from 2015 (two years after the shock) onwards we start seeing a significant difference in the healthcare expenditure between the treatment and the control group. Starting with a difference of -164.21 euro and going up to a difference of -320.03 euro in 2018.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect:				
2013 (β1)	9.65	25.93	0.710	-41.16 – 60.47
2014 (β2)	-34.69	26.30	0.187	-86.23 – 16.86
2015 (β3)	-164.21	28.51	0.000	-220.08 - -108.34
2016 (β4)	-199.44	29.92	0.000	-258.08 - -140.80
2017 (β5)	-278.99	31.56	0.000	-340.85 - -217.14
2018 (β6)	-320.03	36.53	0.000	-391.63 - -248.42

Table 5: the difference-in-difference regression outcome based on equation 3 comparing the yearly difference in total yearly healthcare spending between the treatment and the control group after the income shock.

While in the short run we do not see a significant treatment effect, we see that the longer an individual stays in their new lowered household income, the lower their healthcare expenditure become. This might indicate that initially in the first two years individuals use their savings that can compensate for the loss of income. If that is the case an individual might not have to adapt their spending behavior. When the household income does not recover back to the level of before the shock, savings might no longer be sufficient to cover all costs. When the savings are over an individual could face liquidity issue, or an individual adapts their cost-benefit analysis at the expense of healthcare consumption. As mentioned in chapter 4, in 2015 some new healthcare costs are added in the Zvw basic health insurance plan that can interfere with our analysis and cause this "delayed" effect we observe. We elaborate on this in more details in section 6.3.

To estimate if our results are consistent, we do the same analysis as above, but using two different treatment groups who had an income shock in 2014 or 2015. This means we create a new sample set with a control and treatment group that exist of different individuals as in the first analysis. The results of this analysis can be found in chapter 11.B in the appendix. In the figures of both tests (11B.1 and 11B.2) we observe already that the parallel trend does not hold. The parallel trend test (table B1 and B4) confirms this. We therefore cannot make causal inferences. However, we can observe a similar long-term pattern as in our main analysis, where the treatment effect increases over time.

6.3 Different healthcare costs

In this section we will break down the total healthcare costs into different types of healthcare spending. We will look at the treatment effect on GP care, hospital care, pharmacy, mental care and others. As some healthcare categories in the data set only appear later in the timeline (as indicated in chapter 4), we will exclude them in this analysis. As an extra test we make a new variable that is a sum of the sub categories examined in this section. We do this to compare the sum of these sub categories with the findings of the total healthcare expenditure in section 6.2[6]. Tables 6 and 7 give a summary of the different analyses we do. The detailed analyses and graphs per healthcare type can be found in the appendix in chapter 11.D.

Dependent variable	*Average before 2013*	*Average after 2013*	*Average Costs in 2012*	*Crude Difference-in-Differences*
GP care (C)	€156.60	€181.56	€154.45	
GP care (T)	€152.20	€175.47	€151.71	-€1.69
Hospital care (C)	€1465.48	€1805.49	€1507.12	
Hospital care (T)	€1452.50	€1803.55	€1517.18	-€11.04
Farmacy (C)	€431.40	€461.64	€406.33	
Farmacy (T)	€413.76	€445.05	€388.65	€1.05
Mental care (C)	€212.44	€214.62	€190.48	
Mental care (T)	€320.31	€268.69	€290.61	-€53.70
Others (C)	€336.55	€366.15	€340.88	
Others (T)	€313.14	€353.48	€319.94	€10.74

Table 6: overview of the average cost per type of healthcare before and after 2013 and in the year 2012 for the treatment and control group.

Dependent variable	*Parallel trend*	*Average treatment effect*	*Std. Error*	*Significant*	*95% conf. Interval*
GP costs	Yes	-1.68	0.28	0.000	-3.99 – -2.65
Hospital costs	No	11. 04	15.59	0.479	-19.51 - 41.60
Pharmacy	No	0.86	4.02	0.830	-7.23 – 8.75
Mental care	Yes	-53.81	11.12	0.000	-75.60 - -32.01
Others	No	10.74	2.88	0.000	5.09 – 16.40
Total of sub-cat.	Yes	-32.84	20.65	0.112	-73.31 – 7.63

Table 7: summary overview of the analyses done of the different types of healthcare based on equation 1 and 2. The complete results can be found in the appendix under chapter 10.C.

In table 6 we compare the average healthcare costs of the treatment and control group before and after the shock. All healthcare costs are relatively similar before 2013, with the exemption in mental care. Here we observe that the treatment group before 2013 spend 107.87 euro more on mental healthcare. Mental care is also the only variable that drops in absolute terms by the treatment group. The costs are 320.31 euro before 2013 and 268.69 euro after 2013. This is a difference of 51.62 euro.

[6] The variable total healthcare costs in 6.2 contains all healthcare costs that are included in the Zvw over time. As the Zvw changes at some points in our timeline, the definition of this variable also changes. Therefore, in this chapter we do a quick analysis of the total healthcare costs only using the healthcare services that are present in the Zvw throughout the whole period 2011 to 2018.

In our analyseses (using equation 1, 2, and 3) we see no effect in hospital, pharmaceutical and other care. Both hospital and pharmaceutical care can be considered as high value care. Hospital care contains mostly emergency and specialist care for serious health conditions. This type of care is therefore not a form of luxury care that individual who needs medical help easily forgo. Furthermore, the costs for hospital care are generally very high, exceeding the mandatory deductible threshold easily. Meaning that once a person needs hospital care, the chances that they exceed the mandatory deductible is high. Pharmaceutical care on the other hand is often paid out of pocket, but it entails low individual costs. Yet, the effectiveness and therapeutical benefit is clear to the individual. Besides the effectiveness of a medicine is often high. With a small investment an individual has a very tangible cure for their illness.

GP care, on the contrary, is impacted by an income shock. In the difference-in-differences analysis we observe that the treatment group spends less on GP care after a shock. The average treatment effect is -1.68 euro. This is a relatively small amount compared to the average costs of GP care per individual (see table 6). We also observe that the treatment effect increases over time. In 2018 the treatment effect is -11.78 (table C3 appendix). It is a bit surprising to find an effect on GP care, because GP care is exempted from the mandatory deductible. But the GP also has the function of a gate keeper to specialist care. Meaning that the GP is often the first touch point for a patient. It is possible that when someone faces an income change, they might wait longer or not go the GP at all when confronted with health issues.

The second type of care that is impacted by an income shock is mental care. In the first difference-in-differences analysis (equation 2) we see that the average treatment effect is -53.81 euro. This result is statistically significant. When looking at the yearly average treatment effect (table C12 appendix), we see that the difference between the treatment and control group increases, going from -20.69

euro (not significant) to -84.50 euro (significant). The results become significant from 2014 onwards, so after the first year the income shock took place. Two possible explanations can be given. It could be that individuals value mental healthcare lower than other types of healthcare. The effect of mental healthcare is less directly visible on overall health for an individual than other medical care (that could give more instant relief of pain and discomfort). Especially as many sessions are needed to achieve a result. It might be that because of this characteristic, individuals facing a financial burden cut more easily in mental care services. Another reason might be that we see an effect because many changes happened in mental healthcare within the Zvw in 2013 as discussed in chapter 4, meaning that we measure the effect of the changes in mental healthcare services in the Zvw rather than the effect of an income change. However, the changes in mental care coverage became more generous in 2014, which seems to contradict with the drop we measure in mental healthcare expenditure.

As a check we sum the above-used sub categories (hospital, GP, pharmacy, mental and other care) to compare the outcome of this sum with the variable total healthcare costs used in chapter 6.2. By doing this analysis we only include the variables that are present in the Zvw throughout the period 2011 to 2018[7]. First, we observe that the parallel trend holds. The average treatment effect (equation 1) is -32.84 euro, but not significant. This is a big difference with the treatment effect of -164.61 euro we found in chapter 6.2. Also, in the yearly treatment effect (equation 3) we observe no significant treatment effect. The difference in this result and the results in chapter 6.2 could be explained by the variables we exclude in this analysis. As mentioned in chapter 4, certain types of care only enter in 2015 into the Zvw basic health insurance plan. These variables could potentially influence the results we find in the analysis in chapter 6.2. It is possible that the results we find in 6.2 are the effect of changes in the Zvw basic health insurance plan. However, excluding the care service that change over time in our analysis also does not give us a full picture of the treatment effect. When measuring only

[7] Due to the removal of missing values we have in this analysis 1,120 individuals less in the control group. The number of individuals in the treatment group remains the same

a part of the outcome variable, we are not able to include a substitution effect in our treatment effect. It is possible that the newly added types of care to the Zvw substitute for another types of care. Testing this assumption, nevertheless, is out of the scope of this thesis research.

6.4 Individual characteristics

With the extra analysis we aim to get a better understanding who are the individuals that spend less on healthcare after a large income shock. Some sub-groups might be more sensitive to a large drop change in their household income. In this analysis we look at the relation to an income shock, total healthcare spending and the individual characteristics gender, age, income and nationality. For these analyses we run the same difference-in-differences analyses as in chapter 6.2 but we do this for each sub-group separately. In this section we discuss the main findings. A summary can be found in table 8. The "n" in the table indicated the number of unique observations (number of individuals). Detailed results can be found in the appendix in chapter 11.D.

Dependent variable healthcare costs	*Parallel trend*	*Average treatment effect*	*Std. Error*	*P value*	*99% Conf. Interval*
Men (n=1,206,585)	Yes	-196.49	36.00	0.000	-267.05 – -125.92
Women (n=1,485,737)	yes	-138.58	26.29	0.000	-190.11– -87.05
19-60 (n=1,342,705)	no	-306.87	30.14	0.000	-365.94 - -247.80
61+ (n=1,349,887)	yes	-2.00	31.00	0.984	-58.76 – 62.77
Low-income (n=1,633,112)	Yes	-216.27	40.17	0.000	-295.01 – -137.53
High-Income (n=1,059,480)	Yes	151.59	23.47	0.000	105.59 – 197.58
Born in NL (n=2,448,984)	yes	-168.61	22.46	0.000	-212.63 - -124.60
Born abroad (n=233,608)	Yes	-199.14	79.66	0.135	-275.27 – 36.98

Table 8: summary overview of the analysis done for the different subgroups in the sample set based on equation 1 and 2. The complete analysis can be found in the appendix under chapter 10.D.

For the variable income and age, we need to allocate the individuals in sub-groups. We allocate individuals into the low or high-income group by using a yearly gross household income cap. To set this cap we use the 50th income percentile (around 59000 yearly gross household income[8]).

[8] Due to privacy reasons and risks of revealing personal data the exact income of the 50th quintile cannot be provided.

Everyone with a yearly gross household income of 59000 or lower belongs in the low-income group and all the others in the high-income group. We keep the same definition for treatment and control group as defined in chapter 5.1. We then run the same analysis using equation 1, 2 and 3 for the low-income and high-income sub groups separately. To look at age we divide the sample set into two groups, one of low age (between 19 to 60 years old in 2011) and high-age (61 years and older in 2011). With these definitions we distribute individuals in fairly equally sized categories

Within this analysis we estimate that only the low-income individuals who face an income shock lower their healthcare expenditure. With an average treatment effect of -216.27 euro, the effect is stronger than the average treatment effect of -164.61 euro of the whole sample. Important to note is that the average healthcare costs for the low-income individuals before 2013 were on average higher than in the total sample (based on figures D5 and D6 in the appendix). Meaning that the effect we see diminished as the relative change is lower or similar to the total sample. For the high-income individuals, we see the opposite effect. Here the control group spends significantly more on healthcare than the treatment group. While more wealthy individuals are less likely to be liquidity sensitive or constrained, even after an income drop, it does not clarify why they spend more on healthcare compared to the control group.

While we cannot take any conclusions about the low age group (as the parallel trend assumption does not hold), we still see a stronger pattern in the difference-in-differences analysis compared to the base sample. The older individuals do not spend significantly different from the control group. This pattern could be explained by two factors. Firstly, younger individuals could be more risk takers and forgo therefore healthcare more easily. Secondly, older individuals are more likely to consume expensive care, already surpassing the mandatory deductible threshold. Cutting costs might either be impossible, or not make any difference in the out-of-pocket expenditure of the individual.

Regarding gender we observe that men respond stronger to an income drop than women. Both women and men have a similar average healthcare cost (based on figures D1, D2) before the shock.

This means that the results do not diminish by relative change. Men have a stronger response than the total sample, where women have a lower response than the total sample. This could be due to several reasons. Women can be more risk averse than men or they might value healthcare more. As we use in this analysis the variable household income, it might also be that men are more often the breadwinner and therefore cut costs more easily when faced with an income shock.

We did not find any significant results for the individuals born outside of the Netherlands. However, this might be because the sample size of individuals not born in the Netherlands is relatively small and therefore the analysis is very sensitive for outliers.

7. ROBUSTNESS ANALYSES

In this section we perform several additional analyses to test if our results are driven by the specification choices made. After this test we can conclude that the results hold. For our robustness check we test the effects of the sample selection by changing the definitions of the treatment and the control group. As outcome measure, we look at the total healthcare costs. An overview of the results can be found in table 9. A more detailed outcome can be found in the appendix chapter 10E. With these two analyses we can state that our results hold, or that our analysis might even be an underestimation of the real effects.

Dependent variable healthcare costs	*Parallel trend*	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	Yes	-164.61	21.71	0.000	-207.16 – -122.07
(β1) Robustness check 1	Yes	-299.54	32.20	0.000	-362.65– -236.43
(β1) Robustness check 2	Yes	-244.79	26.41	0.000	-296.55– -193.03

Table 9: comparisons of the difference-in-differences regression outcomes for the main analysis and the robustness checks. Here the outcomes of the regressions of equation 2 are displayed, comparing the average treatment effect of an income drop.

In the first check we change the definition of a stable income to a stricter range. In this analysis a stable income is defined as an income that does not increase or decreases more than 10 percent per year. The definition of an income shock remains the same. For this analysis we see that the parallel trend holds, and that the results also remain significant. We also notice that the effect for the treatment group becomes stronger than compared to the main analysis of this thesis.

In the second robustness check we keep the definition of a stable income the same as before (change of maximum 15 percent) and we make the definition of a household income shock stricter. In this analysis we define the shock as an income drop of at least 25 percent. The effects of an income shock are stronger compared to the main analysis as used in this thesis.

Because both of the robustness analysis measures a stronger treatment effect. It is therefore possible that the estimates in our thesis are an underestimation of the treatment effect.

8. DISCUSSION

In chapter 6.2 we see that our analysis suggests that there is an effect on healthcare expenditure after a large income drop on household level. This could mean that individuals who experience a large income drop face liquidity concerns in their healthcare consumption. It could also mean that individuals who experience a large income shock make a different cost-benefit analysis (possibly as a consequence of liquidity concerns) at the expense of healthcare services. The analysis also measured that the treatment effect only starts two years after the income shock. This possibly suggests that individuals are able to cover their income loss with savings for the first two years, which delays the effect of an income shock.

In chapter 6.3 we measure a treatment effect on GP and mental care only. The effect in GP care is in line with the findings of Beck (1974) who finds a drop in GP services, especially among the poor. While the mandatory deductible does not apply to GP care in our setting, the GP is often the first touch point for an individual when falling ill. A GP can refer a person to see a specialist or prescribe medication. In the Netherlands, 3 percent of the population says to avoid a GP visit, out of fear for possible follow-up costs (Esch et al., 2015). It is therefore possible that the individuals in our analysis reduce GP care out of fear for possible follow-up costs. We also find a treatment effect in mental healthcare. This could indicate that people value mental-care less than other types of care. Remarkably, the mental healthcare costs before the income shock are much higher for the treatment group than the control group. Mental care is also the only type of healthcare of which the treatment group drop in absolute terms after the income shock. The control group in the contrary has a stable mental healthcare expenditure. There findings could point towards an effect caused by income and not by changes in the Zvw.

In chapter 6.3 on the contrary we do not find any effect on hospital care and pharmacy expenditures. Both hospital care and pharmaceuticals can be considered high-value care. That we do not find any treatment effect on these types of care can be therefore seen as positive. This could indicate that individuals who experience a large income cut only costs on low-value care.

When looking at sub-groups in our sample, we notice that men and low-income individual respond the strongest to a large income drop. In the literature we see that women tend to be more risk averse and that they value health more or differently than men. Women tend to be more sensitive to their health needs and they pay more attention to symptoms (Verbrugge,1985). Besides, women tend to be more risk averse, and more likely to utilize preventive care services than men (Vaidya et al., 2012). That low-income groups respond stronger to a large income is in line with the research of Beck (1974) where he finds that poor families respond stronger to a cost-sharing model. This result could indicate that low-income individuals after a large income shock are more likely to face liquidity issues. In chapter 3 we mentioned that there are several subsidies and systems in place for low-income individuals to get financial support to cover expenses for healthcare consumption specifically. These could absorb liquidity issues. But while these subsidies are there in place, it does not mean that low-income individuals applied to receive these subsidies or that they use the subsidies to cover healthcare expenses.

We need to be careful making any causal inferences from our analyses. When we look at the treatment groups who experience a household shock in another year (2014 or 2015) the parallel trend assumption does not hold. In the yearly average treatment effect (table B3 and B6 in the appendix) we see that the treatment effect consistently becomes statistically significant in the year 2015. This diminishes our earlier argument that individuals use their savings after an income shock. The persistence of finding a significant result in 2015 indicates that it is more likely that we measure the effect of an external event. In this case the change in the Zvw basic health insurance plan. This argument becomes stronger when we analyze the sub-categories of care. We notice that care that does not change much within the Zvw (hospital and pharmaceutical care) is not responsive to an income shock. When we estimate the treatment effect of the sum of the sub-categories that are consistently present in the Zvw, we also measure no treatment effect. The only type of care that remains the same in the Zvw basic health insurance plan and shows a treatment effect is GP care. Yet the treatment effect is so small that it is neglectable. Researching the impact of the change in the Zvw is outside of the scope of this thesis and is a point for further research. However, our robustness analysis could give a slight indication. When we analyze the yearly treatment effect in the robustness analyses (table B3 and B6 in the appendix), we see that the treatment effect becomes significant in the year 2014 (before the change in Zvw). This could indicate that there still is an income effect, which is interesting for further research.

While our study suggests a link between income and healthcare expenditure, this link might not be a good comparison. It is a possibility that individual who consume less care are not facing any reverse health outcomes (Gross et al., 2020). Meaning that low-income individuals might be more sensitive to the incentive of a cost-sharing model to cut unnecessary and low-value care. Further research therefore should focus on the health outcomes of individuals who experience a large income drop and as a consequence consume les care.

To conclude, the drop in healthcare expenditure that we find might not per se be caused by an income drop and if it is, then it does not mean that the drop in healthcare expenditure is problematic. It could indicate towards a lack of financial planning and allocation of financial resources of the individuals themselves. It might also indicate that a drop in income cuts "luxury" or "unnecessary" healthcare usage.

8.1 Limitations

Our study has some limitations that possibly influence the results. In this section we discuss the limitations we faced in our research.

Within our sample set we try to select individuals who experience a large income shock based on the gross household income. As we work with information on gross income, we do not know the impact on net income. It is possible that a 20 percent drop in gross income does not result in a large enough change in net household income to be considered as a large income drop to some individuals.

In our dataset we do not have the information explaining the reason for an individual income shock. It is therefore possible that there are individuals in our treatment group who experience an income shock due to a health shock, meaning that the income shock is not exogenous. If that is the case, then the treatment and control group are not equal comparisons. If it is the case that the income drop is linked to a health effect, we measure in our analyses the effect of someone falling ill instead of the effect of an income drop.

In our analyses we are not able to correct for change in the Zvw. As mentioned earlier, this might disrupt our results. It is therefore possible that the effects we measure are due to changes in the Zvw and not due to change in income.

9. Conclusion

With our analyses we aimed to measure the effect of a large income shock at household level on individual healthcare expenditures in a mandatory deductible system. We hypothesized that individual who do experience a large income shock will spend less on healthcare than individuals whose income stays stable. We also expected to see that some types of care would be more affected than others. In this thesis we do indeed measure that individuals who experience an income shock spend less on healthcare after the income shock compared to individuals whose income stay stable. We also measure that while some types of care are impacted, the expenditure of other types of care remain unchanged. The care that is mostly impacted are GP and mental healthcare services. The effect seems to be the biggest in mental healthcare services. This could indicate that individual see mental care services as low-value care and therefore forgo this type of care more easily after an income loss. While we carefully stated that there might be an effect caused by an income drop, we also pointed to possible external changes happening to the basic health insurance plans that might interfere with our results. We conclude that a causal inference is not possible with this research and that further research is needed.

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11. Appendix

11. A. Data creation and cleaning procedure

As described in chapter 4, we use the dataset that contains the individual information about income. In this dataset many types of income are listed, however we choose to remove them all and only use the information about the yearly gross household income. In this set we remove individuals who had information about their yearly gross household income missing as they might distort our analysis. We removed individuals who had a negative income at some point in time. These are administrative errors and will distort our analysis.

When the income information is ready, we prepare the dataset that contains all healthcare cost information. Due to the size of this dataset we firstly had to remove many variables that we do not use. Initially we only kept the total healthcare expenditure (minus the GP registration fee). When we analyzed the subcategories, we added them individually back into our sample. For the total healthcare costs, we removed the individuals who had missing information at some point of time in the dataset or who had negative healthcare costs due to an administrative error.

We merged then both sets together, including the dataset that contains the individual characteristics (using only the variables gender, year- and country of birth) and the dataset that includes information on the voluntary deductible. We merge the datasets with the income dataset based on the variable called RINPERSOON. This variable is a unique personal code. When we merge the datasets, 4,497,304 individuals could not be found in the income dataset, but they did exist in the other datasets. These are individuals we removed during the cleaning process. An additional 504 individuals were removed in the dataset healthcare costs, individual characteristics and voluntary deductible due to missing values. Once the datasets were merged, we removed the individuals who ever had a voluntary deductible and we removed individuals who were born after 1992.

11.B Main analysis using household income shock in 2014 and 2015

Graphs:

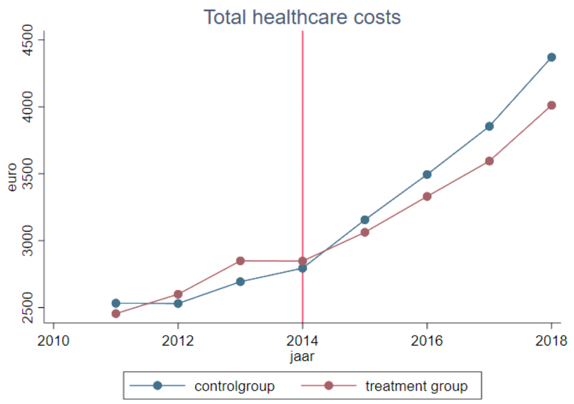

Figure B1: Average total healthcare expenditure for the treatment and control group with an income shock for the treatment group in 2014.

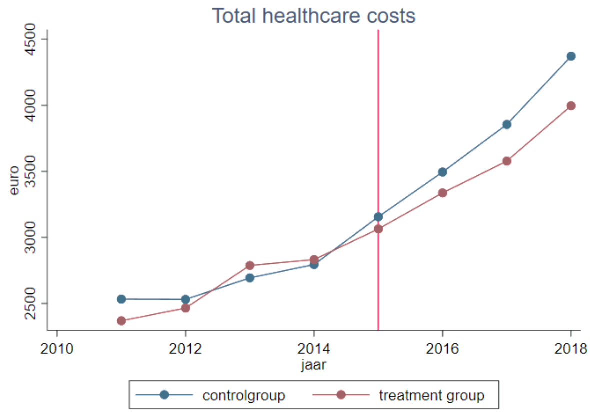

Figure B2: Average total healthcare expenditure for the treatment and control group with an income shock for the treatment group in 2015.

Difference-in-differences regressions:

2014

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-233.50	34.67	0.000	-301.46 – -165.54
2013 (β3)	-86.37	33.64	0.010	-152.32 – -20.42
2014 (β4)	-102.52	34.54	0.003	-170.21 – -34.83
2015 (β5)	-248.56	36.56	0.000	-320.89 - -176.23
2016 (β6)	-319.90	38.56	0.000	-395.48- -244.32
2017 (β7)	-415.85	39.69	0.000	-493.64 - -338.06
2018 (β8)	-515.36	43.43	0.000	-600.49 - -430.24

TableB1: parallel trend based on equation 1 where the treatment group experiences an income shock in 2014.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-213.81	22.99	0.000	-258.99 – -168.75

Table B2: difference-in-differences regression based on equation 2, measuring the average treatment effect, where the treatment group experiences an income shock in 2014

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect:				
2014 (β1)	4.10	27.70	0.882	-50.18 – 58.39
2015 (β2)	-141.93	29.53	0.000	-199.82 – -84.05
2016 (β3)	-213.27	31.23	0.000	-274.48 - -152.07
2017 (β4)	-309.22	32.62	0.000	-373.15- -245.29
2018 (β5)	-408.74	36.91	0.000	-481.07 - -336.40

Table B3: difference-in-differences regression based on equation 2, measuring the yearly treatment effect, where the treatment group experiences an income shock in 2014

2015

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-201.39	32.50	0.000	-265.09 – -137.69
2013 (β3)	-102.83	34.08	0.003	-169.75 – -35.90
2014 (β4)	56.72	34.07	0.096	-10.07 – 123.51
2015 (β5)	-129.14	32.34	0.000	-192.52 – -65.76
2016 (β6)	-195.60	35.18	0.000	-264.59- -126.62
2017 (β7)	-313.91	38.66	0.000	-389.68 - -238.14
2018 (β8)	-412.59	41.48	0.000	-493.88 - -331.29

TableB4: parallel trend based on equation 1 where the treatment group experiences an income shock in 2015.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-200.93	23.56	0.000	-247.12 – -154.75

Table B5: difference-in-differences regression based on equation 2, measuring the average treatment effect, where the treatment group experiences an income shock in 2015.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2015 (β1)	-67.26	28.07	0.017	-122.27 – -12.26
2016 (β2)	-133.73	29.97	0.000	-192.47- -74.98
2017 (β3)	-252.03	33.18	0.000	-317.07- -186.99
2018 (β4)	-350.71	36.39	0.000	-422.04 - -279.38

Table B6: difference-in-differences regression based on equation 2, measuring the yearly treatment effect, where the treatment group experiences an income shock in 2015.

11.C Graphs and Difference-In-Differences analysis of types of care

Graphs:

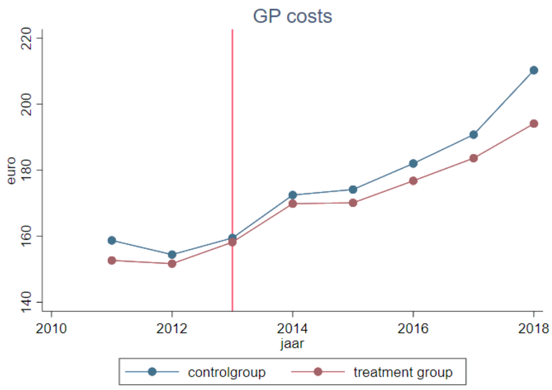

Figure C1: Average GP care expenditure per year for the treatment and control group with an income shock for the treatment group in 2013.

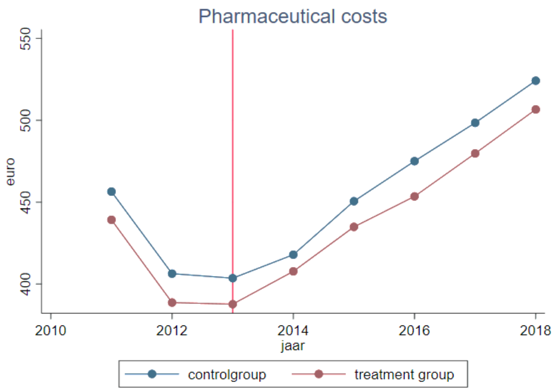

Figure C2: Average Pharmaceutical care expenditure per year for the treatment and control group with an income shock for the treatment group in 2013.

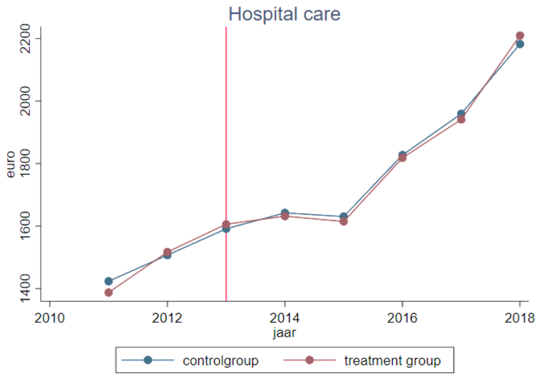

Figure C3: Average hospital care expenditure per year for the treatment and control group with an income shock for the treatment group in 2013.

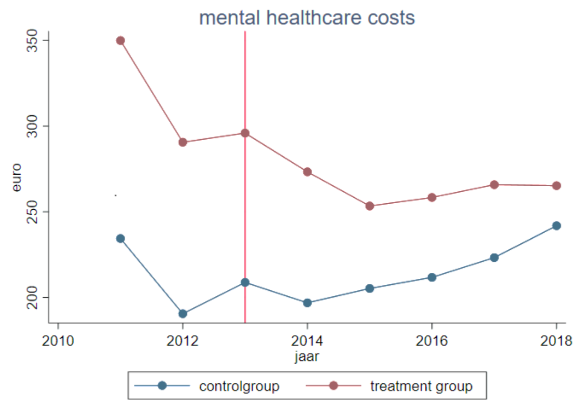

Figure C4: Average mental care expenditure per year for the treatment and control group with an income shock for the treatment group in 2013.

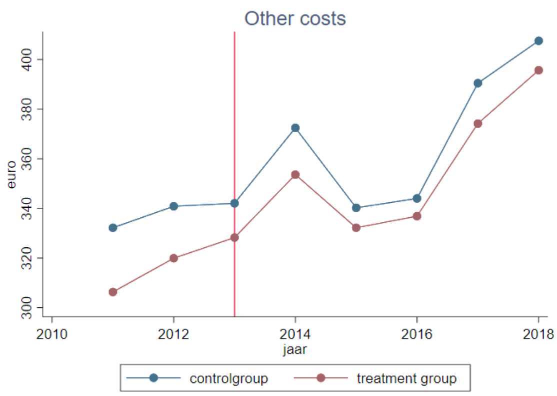

Figure C5: Average other healthcare expenditure per year for the treatment and control group with an income shock for the treatment group in 2013.

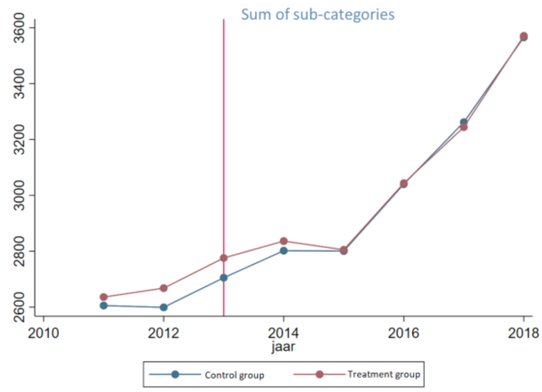

Figure C6: average total healthcare costs based on the sum of the sub categories (GP, hospital, mental, pharmaceutical and other care). Showing the average of the treatment and control group per year.

Difference-in-differences regressions:

GP care

Dependent variable GP costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-3.32	0.34	0.000	-3.99– -2.65
2013 (β3)	1.46	0.35	0.000	0.77– 2.15
2014 (β4)	0.12	0.40	0.761	-0.66– 0.91
2015 (β5)	-1.29	0.42	0.002	-2.10 – -0.47
2016 (β6)	-2.50	0.44	0.000	-3.35- -1.64
2017 (β7)	-4.39	0.46	0.000	-5.30- -3.48
2018 (β8)	-13.44	0.53	0.000	-14.48 –12.41

TableC1: parallel trend based on equation 1 comparing the GP costs of the treatment and control group.

Dependent variable GP costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-1.68	0.28	0.000	-2.23– -1.12

Table C2: difference-in-differences regression based on equation 2, measuring the average treatment effect for the GP costs.

Dependent variable GP costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	3.12	0.32	0.000	2.50 – 3.75
2014 (β2)	1.78	0.37	0.000	1.07 – 2.50
2015 (β3)	0.37	0.38	0.328	-0.37 – 1.12
2016 (β4)	-0.83	0.40	0.039	-1.62- -0.04
2017 (β5)	-2.73	0.43	0.000	-3.57- -1.88
2018 (β6)	-11.78	0.50	0.000	-12.76 - -10.80

Table C3: difference-in-differences regression based on equation 2, measuring the yearly treatment effect for the GP costs.

Hospital care

Dependent variable hospital costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-46.07	21.30	0.031	-87.81 – -4.33
2013 (β3)	4.43	22.40	0.843	-39.47 – 48.33
2014 (β4)	-20.56	22.56	0.362	-64.77 – 23.66
2015 (β5)	-25.88	23.75	0.276	-72.43 – 20.67
2016 (β6)	-19.15	24.91	0.442	-67.97- 29.67
2017 (β7)	-28.18	25.45	0.268	-78.05 – 21.70
2018 (β8)	17.39	29.26	0.552	-39.95 – 74.73

TableC4: parallel trend based on equation 1 comparing the hospital costs of the treatment and control group.

Dependent variable hospital costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	11.04	15.59	0.479	-19.51 – 41.60

Table C5: difference-in-differences regression based on equation 2, measuring the average treatment effect for the hospital costs.

Dependent variable Healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	27.47	19.72	0.164	-11.19 – 66.12
2014 (β2)	2.48	19.73	0.900	-36.19 – 41.15
2015 (β3)	-2.85	20.97	0.892	-43.95 – 38.26
2016 (β4)	3.89	22.19	0.861	-39.61 –47.38
2017 (β5)	-5.14	22.71	0.821	-49.66 – 39.37
2018 (β6)	40.42	26.94	0.134	-12.38 – 93.23

Table C6: difference-in-differences regression based on equation 2, measuring the yearly treatment effect for the hospital costs.

Pharmacy

Dependent variable pharmacy costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	0.43	4.07	0.915	-7.54 – 8.41
2013 (β3)	1.78	2.83	0.530	-3.77 – 7.33
2014 (β4)	7.48	3.54	0.035	0.54 – 14.43
2015 (β5)	2.00	4.90	0.684	-7.61 – 11.60
2016 (β6)	-3.88	4.87	0.426	-13.43 – 5.68
2017 (β7)	-1.03	5.28	0.846	-11.37 – 9.32
2018 (β8)	0.12	7.03	0.986	-13.65 – 13.89

TableC7: parallel trend based on equation 1 comparing the pharmaceutical costs of the treatment and control group.

Dependent variable pharmacy costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	0.86	4.02	0.830	-7.02 – 8.75

Table C8: difference-in-differences regression based on equation 2, measuring the average treatment effect for the hospital costs.

Dependent variable pharmacy costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	1.56	3.13	0.619	-4.58 – 7.70
2014 (β2)	7.27	3.69	0.049	0.03 – 14.50
2015 (β3)	1.78	5.08	0.729	-8.17 – 11.73
2016 (β4)	-4.09	4.94	0.408	-12.78 – 5.60
2017 (β5)	-1.24	5.44	0.819	-11.91 – 9.43
2018 (β6)	-0.10	7.23	0.989	-14.27 – 14.08

Table C9: difference-in-differences regression based on equation 2, measuring the yearly treatment effect for the hospital costs.

Mental care

Dependent variable mental care costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	15.49	17.40	0.373	-18.62 – 49.60
2013 (β3)	-12.94	14.46	0.371	-41.28 – 15.40
2014 (β4)	-23.65	15.38	0.124	-53.78 – 6.49
2015 (β5)	-51.98	14.61	0.000	-80.61 – 24.35
2016 (β6)	-53.49	15.03	0.000	-82.95 – 24.63
2017 (β7)	-57.55	15.27	0.000	-87.47 - -27.63
2018 (β8)	-76.75	15.28	0.000	-106.71 - -46.79

TableC10: parallel trend based on equation 1 comparing the mental care costs of the treatment and control group.

Dependent variable mental care costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-53.81	11.12	0.000	-75.60 – -32.01

Table C11: difference-in-differences regression based on equation 2, measuring the average treatment effect for the mental care costs.

Dependent variable mental care costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	-20.69	13.72	0.132	-47.58 – 6.20
2014 (β2)	-31.40	14.12	0.026	-59.07 - -3.72
2015 (β3)	-59.73	13.40	0.000	-85.99 - -33.46
2016 (β4)	-61.23	13.67	0.000	-88.03 - -34.43
2017 (β5)	-65.30	14.17	0.000	-93.07 - -37.53
2018 (β6)	-84.50	13.94	0.000	-111.82 - -57.17

Table C12: difference-in-differences regression based on equation 2, measuring the yearly treatment effect for the mental care costs.

Others

Dependent variable other care costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-4.94	3.90	0.205	-12.58– 2.70
2013 (β3)	7.12	4.66	0.126	-2.01 – 16.26
2014 (β4)	2.10	4.28	0.624	-6.28 – 10.48
2015 (β5)	12.90	4.44	0.004	4.20 – 21.60
2016 (β6)	13.80	4.39	0.002	5.19 – 22.40
2017 (β7)	4.66	5.25	0.374	-5.63 – 14.95
2018 (β8)	9.07	5.15	0.078	-1.03 – 19.17

TableC13: parallel trend based on equation 1 comparing the other care costs of the treatment and control group.

Dependent variable other care costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β3) in equation 2	-10.74	2.88	0.000	5.09 – 16.40

Table C14: difference-in-differences regression based on equation 2, measuring the average treatment effect for the other care costs.

Dependent variable other care costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	9.59	4.13	0.020	1.49 – 17.69
2014 (β2)	4.57	3.67	0.214	-2.63 – 11.77
2015 (β3)	15.37	3.85	0.000	7.82 – 22.91
2016 (β4)	16.26	3.76	0.000	8.89 – 23.62
2017 (β5)	7.13	4.75	0.133	-2.17 – 16.43
2018 (β6)	11.54	4.64	0.013	2.46 – 20.63

Table C15: difference-in-differences regression based on equation 2, measuring the yearly treatment effect for the other care costs.

Total

Dependent variable total care costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-38.41	28.67	0.180	-94.61 – 17.80
2013 (β3)	1.85	28.07	0.947	-53.16 – 56.86
2014 (β4)	-34.51	28.90	0.233	-91.16 – 22.14
2015 (β5)	-64.26	29.85	0.031	-122.76 - -5.76
2016 (β6)	-65.22	31.11	0.036	-126.19 - -4
2017 (β7)	-86.49	32.08	0.007	-149.37 - -23.61
2018 (β8)	-63.62	35.73	0.075	-133.65 – 6.41

TableC16: parallel trend based on equation 1 comparing the sum of the sub categories of care costs of the treatment and control group

Dependent variable total costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-32.84	20.65	0.112	-73.31 – 7.63

Table C17: difference-in-differences regression based on equation 2, measuring the average treatment effect for the sum costs of the sub categories of care.

Dependent variable total costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	21.05	25.38	0.407	-28.69 – 70.79
2014 (β2)	-15.30	25.69	0.551	-65.66 – 35.05
2015 (β3)	-45.06	26.77	0.092	-95.52 – 7.40
2016 (β4)	-46.02	27.98	0.100	-100.85 – 8.81
2017 (β5)	-67.28	29.18	0.021	-124.47- -10.10
2018 (β6)	-44.42	33.11	0.180	-109.31 – 20.47

Table C18: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the sum costs of the sub categories of care.

11.D Graphs and Difference-In-Differences analysis of total healthcare costs based on different personal characteristics

Graphs:

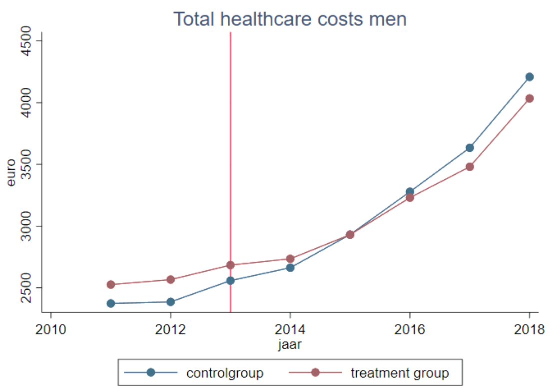

Figure D1: Average total healthcare expenditure per year for men.

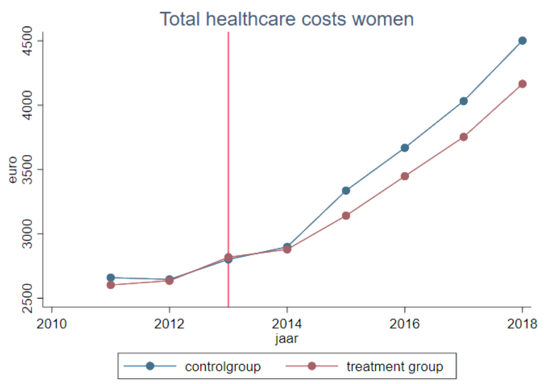

Figure D2: Average total healthcare expenditure per year for women.

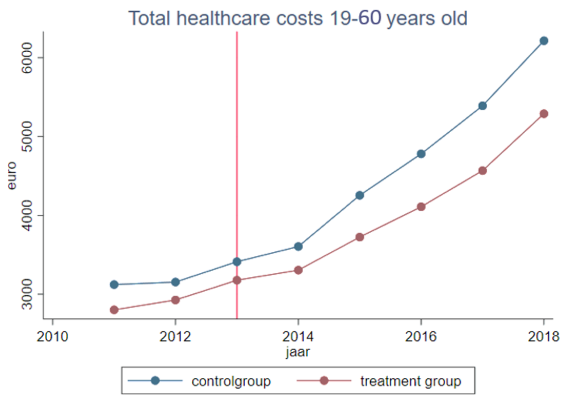

Figure D3: Average total healthcare expenditure per year for young individuals between 19 to 60 years old.

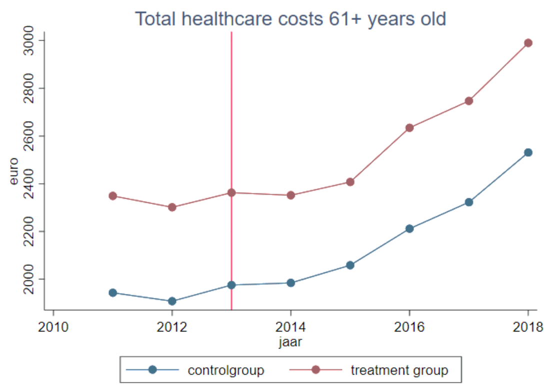

Figure D4: Average total healthcare expenditure per year for individuals 61 year and older.

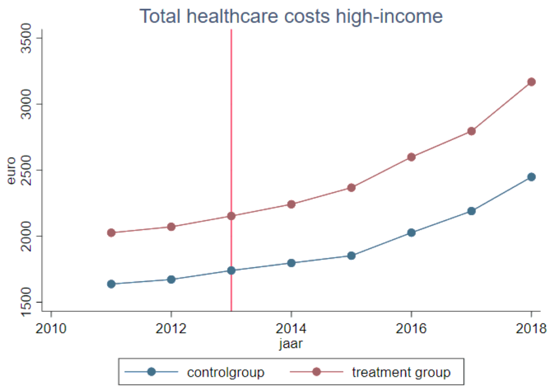

Figure D5: Average total healthcare expenditure per year for individuals with a high income (>59000 per year).

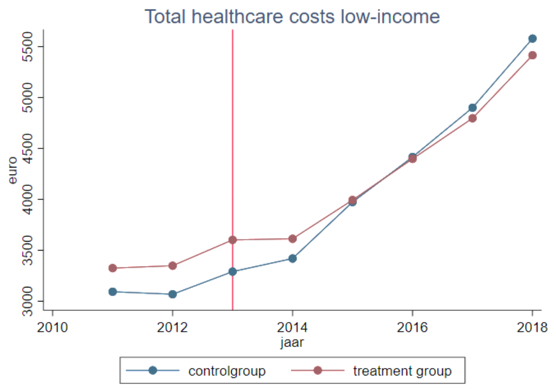

Figure D6: Average total healthcare expenditure per year for individuals with a low income (<59000 per year).

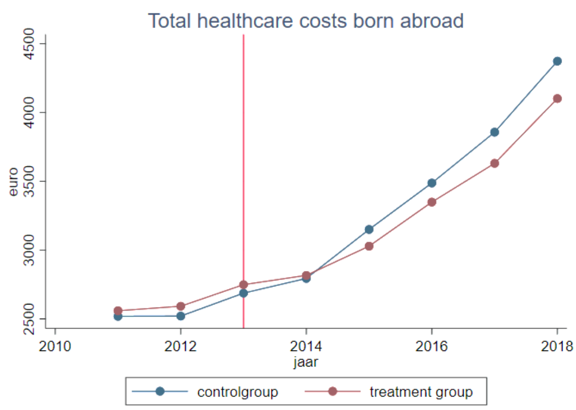

Figure D7: Average total healthcare expenditure per year for individuals born abroad.

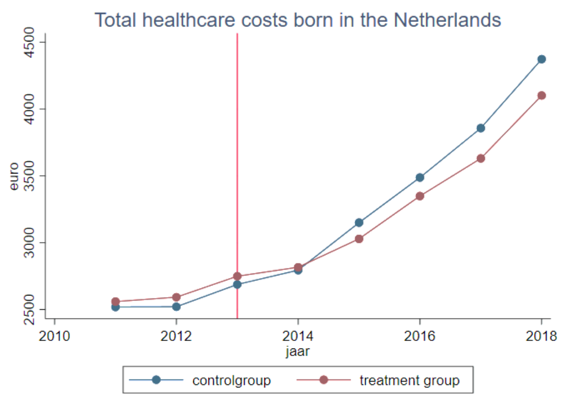

Figure D8: Average total healthcare expenditure per year for individuals born in the Netherlands

Difference-in-differences regressions:

Men

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-27.88	48.35	0.565	-122.94 – 67.18
2013 (β3)	-54.84	47.35	0.246	-147.65 – 37.97
2014 (β4)	-108.56	48.37	0.025	-203.37 - -13.76
2015 (β5)	-181.46	51.72	0.000	-282.82 - -80.09
2016 (β6)	-228.42	53.91	0.000	-334.08 - -122.76
2017 (β7)	-334.39	54.51	0.000	-441.22 - -227.56
2018 (β8)	-354.91	63.76	0.000	-479.88 - -229.93

TableD1: parallel trend regression based on equation 1 comparing the total healthcare costs for men.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-196.49	36.00	0.000	-267.05 – -125.92

Table D2: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs for men.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	-40.91	42.89	0.340	-124.96 – 43.16
2014 (β2)	-94.62	43.04	0.028	-178.98 – 10.26
2015 (β3)	-167.52	47.14	0.000	-259.92 - -75.12
2016 (β4)	-214.48	49.13	0.000	-310.77 - -118.18
2017 (β5)	-320.44	49.90	0.000	-418.25 - -22.64
2018 (β6)	-340.97	59.98	0.000	-458.52 - -223.41

Table D3: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for men.

Women

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-45.98	33.86	0.174	-112.34– 20.38
2013 (β3)	27.80	34.42	0.805	-39.67 – 95.27
2014 (β4)	-8.91	36.08	0.096	-79.62 – 61.79
2015 (β5)	-184.31	38.33	0.000	-259.43 - -131.18
2016 (β6)	-210.01	40.22	0.000	-288.85 - -182.89
2017 (β7)	-268.05	43.45	0.000	-353.20 - -232.37
2018 (β8)	-325.93	47.74	0.000	-419.49 - -232.37

TableD4: parallel trend regression based on equation 1 comparing the total healthcare costs for women.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-138.58	26.29	0.000	-190.11– -87.05

Table D5: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs for men.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	50.79	31.51	0.107	-10.96 – 112.55
2014 (β2)	14.08	32.37	0.664	-49.38 – 77.53
2015 (β3)	-161.33	34.65	0.000	-229.24 – -93.41
2016 (β4)	-187.02	36.68	0.000	-258.92 - -115.13
2017 (β5)	-245.06	40.34	0.000	-324.12 - -166.00
2018 (β6)	-302.94	44.81	0.000	-390.76 – 215.12

Table D6: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for women.

19-60 years old

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-93.03	36.89	0.012	-165.33 - -20.73
2013 (β3)	-7.02	39.41	0.859	-84.26 – 70.22
2014 (β4)	-72.11	42.42	0.089	-155.25 – 11.02
2015 (β5)	-303.11	46.48	0.000	-394.21 - -212.01
2016 (β6)	-443.78	47.61	0.000	-537.09 - -350.47
2017 (β7)	-595.26	51.31	0.000	-695.82 - -494.70
2018 (β8)	-699.03	59.63	0.000	-815.89 - -582.16

Table D7: parallel trend regression based on equation 1 comparing the total healthcare costs for individuals between 19-60 years old.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-306.87	30.14	0.000	-365.94 - -247.80

Table D8: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs for individuals between 19-60 years old.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	39.49	35.56	0.267	-30.21 – 109.20
2014 (β2)	-25.60	37.93	0.500	-99.94 – 48.75
2015 (β3)	-256.60	42.14	0.000	-339.19 - -174.00
2016 (β4)	-397.26	43.58	0.000	-482.68 - -311.85
2017 (β5)	-548.75	47.54	0.000	-641.93 - -455.57
2018 (β6)	-652.51	56.46	0.000	-763.18 - -541.84

Table D9: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for individuals between 19-60 years old.

61+ years old

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	12.38	43.52	0.776	-71.92 – 97.69
2013 (β3)	-6.33	41.03	0.877	-86.75 – 74.08
2014 (β4)	-26.21	40.87	0.521	-106.32 – 53.90
2015 (β5)	-44.65	42.33	0.292	-127.61 – 38.32
2016 (β6)	29.21	45.18	0.521	-59.03 – 118.06
2017 (β7)	31.12	45.45	0.493	-57.95 – 120.20
2018 (β8)	65.72	50.08	0.189	-32.44 – 163.88

Table D10: parallel trend regression based on equation 1 comparing the total healthcare costs for individuals of 61 years and older

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-2.00	31.00	0.984	-58.76 – 62.77

Table D11: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs for individuals of 61 years and older.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	-12.52	37.58	0.739	-86.17 – 61.13
2014 (β2)	-32.40	36.45	0.374	-103.85 – 39.05
2015 (β3)	-50.84	38.48	0.186	-126.25 – 24.58
2016 (β4)	23.32	40.97	0.569	-56.98 – 103.63
2017 (β5)	24.93	41.58	0.549	-56.57 – 106.43
2018 (β6)	59.53	46.52	0.201	-31.66 – 150.71

Table D12: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for individuals of 61 years and older.

Low-income

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-48.34	52.58	0.358	-151.40 – 54.73
2013 (β3)	31.08	51.70	0.548	-70.26 – 132.42
2014 (β4)	-86.33	53.33	0.106	-190.87 – 18.20
2015 (β5)	-260.48	57.02	0.000	-372.24 - -148.73
2016 (β6)	-298.74	58.89	0.000	-414.16 - -183.31
2017 (β7)	-383.71	62.67	0.000	-506.54 - -260.89
2018 (β8)	-444.42	69.93	0.000	-581.49 - -307.35

Table D13: parallel trend regression based on equation 1 comparing the total healthcare costs for individuals with a yearly gross household income in 2012 lower than 59000 euro.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-216.27	40.17	0.000	-295.01 – -137.53

Table D14: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs for individuals with a yearly gross household income in 2012 lower than 59000 euro.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	55.26	47.70	0.247	-38.25 – 148.74
2014 (β2)	-62.17	48.66	0.201	-157.54 – 33.21
2015 (β3)	-236.32	52.37	0.000	-338.96 - -133.67
2016 (β4)	-274.57	54.33	0.000	-381.05 - -168.09
2017 (β5)	-359.55	58.38	0.000	-473.98 - -245.11
2018 (β6)	-420.25	65.98	0.000	-549.58 - -290.92

Table D15: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for individuals with a yearly gross household income in 2012 lower than 59000 euro.

High-Income

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-10.35	31.49	0.742	-72.06 – 51.36
2013 (β3)	13.93	31.68	0.660	-48.16 – 76.02
2014 (β4)	46.06	32.85	0.161	-18.33 – 110.44
2015 (β5)	116.77	34.87	0.001	48.43 – 185.12
2016 (β6)	174.14	37.04	0.000	101.55 – 246.73
2017 (β7)	206.39	37.58	0.000	132.74 – 280.05
2018 (β8)	321.19	43.68	0.000	235.58 – 406.81

Table D16: parallel trend regression based on equation 1 comparing the total healthcare costs for individuals with a yearly gross household income in 2012 higher than 59000 euro.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	151.59	23.47	0.000	105.59 – 197.58

Table D17: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs for individuals with a yearly gross household income in 2012 higher than 59000 euro.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	19.10	28.32	0.500	-36.40 – 74.60
2014 (β2)	51.23	28.52	0.072	-4.66 – 107.12
2015 (β3)	121.95	31.20	0.000	60.79 – 183.10
2016 (β4)	179.32	33.26	0.000	114.13 – 244.51
2017 (β5)	211.57	34.12	0.000	144.67 – 278.47
2018 (β6)	326.37	40.84	0.000	246.31 – 406.42

Table D18: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for individuals with a yearly gross household income in 2012 higher than 59000 euro.

Born in the Netherlands

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-30.86	30.31	0.309	-90.27 – 28.55
2013 (β3)	-9.88	29.61	0.793	-167.91 – 48.15
2014 (β4)	-49.41	30.97	0.111	-110.12 – 11.28
2015 (β5)	-192.98	32.61	0.000	-256.90 - -129.06
2016 (β6)	-210.31	34.33	0.000	-277.59 - -143.02
2017 (β7)	-298.16	35.66	0.000	-368.06 - -228.27
2018 (β8)	-343.53	40.44	0.000	-422.79 - -264.27

Table D19: parallel trend regression based on equation 1 comparing the total healthcare costs for individuals born in the Netherlands.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-168.61	22.46	0.000	-212.63 - -124.60

Table D20: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs for individuals born in the Netherlands.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	5.56	26.83	0.836	-47.02 – 58.14
2014 (β2)	-33.98	27.66	0.219	-88.20 – 20.24
2015 (β3)	-177.55	29.57	0.000	-235.50 – -119.60
2016 (β4)	-194.87	31.31	0.000	-256.23 - -133.52
2017 (β5)	-282.73	32.93	0.000	-347.26 – -218.20
2018 (β6)	-328.10	37.99	0.000	-402.55 - -253.64

Table D21: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for individuals born in the Netherlands.

Not born in the Netherlands

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-105.65	88.33	0.232	-278.78 – 67.47
2013 (β3)	-0.19	101.42	0.999	-198.98 – 198.60
2014 (β4)	-83.09	95.05	0.382	-269.40 – 103.21
2015 (β5)	-88.78	111.80	0.427	-307.90 – 130.34
2016 (β6)	-289.66	110.99	0.009	-507.21 - -72.11
2017 (β7)	-284.27	119.70	0.018	-518.88 - -49.65
2018 (β8)	-285.85	137.27	0.037	-554.89 - -16.80

Table D22: parallel trend regression based on equation 1 comparing the total healthcare costs for individuals not born in the Netherlands.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-199.14	79.66	0.135	-275.27 – 36.98

Table D23: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs for individuals not born in the Netherlands.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	52.64	95.05	0.580	-133.65 – 135.93
2014 (β2)	-30.27	84.79	0.721	-196.45 – 135.92
2015 (β3)	-35.95	102.71	0.726	-237.26 – 165.35
2016 (β4)	-236.83	100.95	0.019	-434.70 - -38.97
2017 (β5)	-231.44	109.01	0.034	-445.10 - -17.78
2018 (β6)	-233.02	129.29	0.072	-486.42 – 20.39

Table D24: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for individuals not born in the Netherlands.

11.E Robustness check

Graphs:

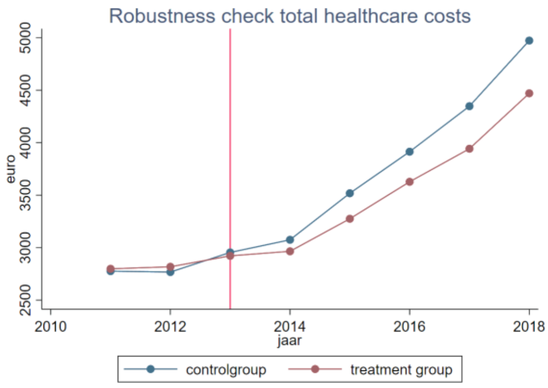

Figure E1: Average total healthcare expenditure per year for the first robustness check.

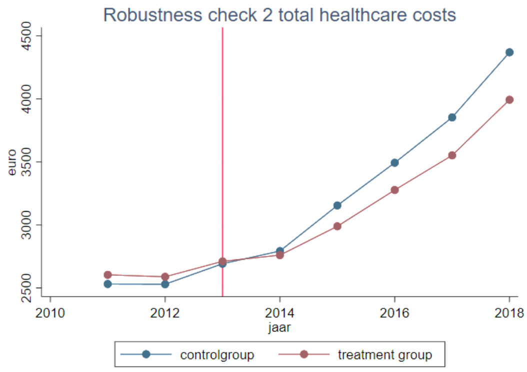

Figure E2: Average total healthcare expenditure per year for the second robustness check.

Difference-in-differences regressions:

Robustness check1

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	-27.88	44.40	0.530	-114.90 – 59.14
2013 (β3)	-82.81	41.24	0.045	-163.65 – -1.97
2014 (β4)	-159.94	43.22	0.000	-244.65 - -75.22
2015 (β5)	-293.35	46.44	0.000	-384.37 - -202.32
2016 (β6)	-336.79	49.00	0.000	-432.84 - -240.74
2017 (β7)	-455.54	50.38	0.000	-554.28 - -356.8
2018 (β8)	-552.45	56.09	0.000	-662.38 - -442.51

Table E1: parallel trend regression based on equation 1 comparing the total healthcare costs for the treatment and control group for the first robustness check. In this regression a stable gross household income is defined as an income that does not change more than 10%.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-299.54	32.20	0.000	-362.65– -236.43

Table E2: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs the treatment and control group. In this regression a stable gross household income is defined as an income that does not change more than 10%.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	-68.87	37.15	0.064	-141.69 – 3.94
2014 (β2)	-146.00	38.12	0.000	-220.70 - -71.29
2015 (β3)	-279.41	41.84	0.000	-361.42 - -197.40
2016 (β4)	-322.85	44.71	0.000	-410.49 - -235.21
2017 (β5)	-441.60	46.36	0.000	-532.47 - -350.74
2018 (β6)	-538.51	52.47	0.000	-641.35 - -435.66

Table E3: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for the treatment and control group. In this regression a stable gross household income is defined as an income that does not change more than 10%.

Robustness check2

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
2011 (β1)	13.85	35.29	0.695	-55.32 – 83.02
2013 (β3)	-39.86	33.76	0.238	-106.02 – 26.30
2014 (β4)	-91.65	34.79	0.008	-159.84 - -23.47
2015 (β5)	-224.60	37.96	0.000	-299.00 - -150.20
2016 (β6)	-275.26	39.27	0.000	-352.22 - -198.29
2017 (β7)	-360.21	41.01	0.000	-440.59 - -279.83
2018 (β8)	-435.59	44.85	0.000	-523.48 - -347.69

Table E4: parallel trend regression based on equation 1 comparing the total healthcare costs for the treatment and control group for the second robustness check. In this regression the treatment group experiences at least an income drop of 25%.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Average treatment effect (β1) in equation 2	-244.79	26.41	0.000	-296.55– -193.03

Table E5: difference-in-differences regression based on equation 2, measuring the average treatment effect for the total healthcare costs the treatment and control group. In this regression the treatment group experiences at least an income drop of 25%.

Dependent variable healthcare costs	*Coefficient*	*Std. Error*	*P value*	*95% Conf. Interval*
Treatment effect equation 3:				
2013 (β1)	-46.79	30.79	0.129	-107.13 – 13.56
2014 (β2)	-98.58	31.11	0.002	-159.55 - -37.61
2015 (β3)	-231.52	34.78	0.000	-299.68 - -163.37
2016 (β4)	-282.18	0.000	0.000	-351.72 - -211.64
2017 (β5)	-367.13	0.000	0.000	-441.49 - -292.78
2018 (β6)	-442.51	0.000	0.000	-524.91 - -360.11

Table E6: difference-in-differences regression based on equation 3, measuring the yearly treatment effect for the total healthcare costs for the treatment and control group. In this regression the treatment group experiences at least an income drop of 25%.