Master Thesis

The Dutch risk equalization model and predictable profits:

are students and higher educated individuals profitable?

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Abstract

In 2006 a new health insurance system was introduced in the Netherlands. This system comprises mandatory insurance, community rated premiums and open enrollment. Due to this new health insurance system, both incentives and the number of instruments for risk selection increased and a risk equalization model was implemented to overcome those incentives. Nevertheless, this model has been shown to predict healthcare cost imperfect and risk selection may still be profitable. Furthermore, two health insurers introduced health insurance aimed on students and individuals with a higher education imposing the presence of profits due to risk selection. In this research we focus on whether students and individuals with a higher education are profitable, given the current risk adjustment model used in the Netherlands. Using data from an annual health survey, healthcare costs are calculated and a replica of the risk adjustment model in the Netherlands is build. Applying t-test between predicted and actual healthcare costs reveals whether there are predictable profits for students and higher educated. Results show that statistically significant predictable profits are present for students (€137), and absent for higher educated (€27).

Acknowledgements

This master thesis was written during my master ‘Health Economics’ at the Erasmus University in Rotterdam. Since my interests lie within the topic of health insurance, I was very glad I got the opportunity to do research about the risk adjustment model in the Netherlands. When I started, I knew this research would become a great challenge for my analytic skills, which was in fact one of the reasons to choose this subject. I see challenges as a way to learn and to improve my skills and experience. During the process I learned a lot in various areas, one of which was that I made the right choice of subject. What I also learned was that I could not have written my thesis without the help of certain people which I would like to thank.

In particular I would like to thank my supervisor René van Vliet. The various discussions and his contributions to my work helped me through the process of writing my thesis. He also managed to challenge me over and over again to improve the quality of my thesis. Without him I would not be able to write the thesis at it is now. Furthermore, I want to thank Pieter Jonkman and Wim Kuijsten for their comments on both the content and the structure of my work. And last but not least, I want to thank my wife Jolanda for her persistent support during my work.

1. Introduction

In the Netherlands, the government introduced a new health insurance system in 2006. The *Health Insurance Act* (Zvw) introduced a system with mandatory insurance, community rated premiums and open enrollment. With this new system the government allowed for regulated competition, following the path that was chosen in the 90's (Van de Ven & Schut 2007). Health insurers are allowed to make profits and are subject to regulated competition for customers. This results in a competition based on premiums and quality of the health insurance. Since quality measures are still on the rise, practice shows that competition primarily takes place based on the premium of the health insurance.

The introduction of community rated premiums was based on possible negative side-effects of competition in the health insurance market. Health insurance, and therefore healthcare, could otherwise become inaccessible for high risks and the quality of care for high risks is likely to decrease when premium differentiation is allowed. Consequence of community rated premiums is, that the premium does not reflect the expected healthcare costs of a certain insured individual. So, individuals with lower expected healthcare costs than their premium are predictably profitable for health insurers. The other way around is also true: unhealthy individuals are predictably unprofitable. Insurance companies are therefore more interested in healthy than unhealthy individuals. Therefore, selecting healthy individuals may be profitable for the health insurer, as is getting rid of the unhealthy insured.

To prevent selection by the health insurer and make cross subsidies between high and low risks possible, the government has implemented a risk equalization system. This system was based on the system which was used in the 10 years before the Health Insurance Act. (Van de Ven & Schut 2007; Prinsze e.a. 2005). This system is used to adjust for differences in health risk of individuals, using equalization payments and thereby decreases the incentive for selection. To calculate those equalization payments, a risk equalization model is used based on several health-related factors as age, gender and prior use of healthcare. With this model the expected healthcare costs for every individual are calculated a priori, which results in a prediction of healthcare costs in the upcoming year (VWS 2007). In addition, a nominal premium is set, which reflects half of the average costs of the population older than 18 years. When the predicted costs are higher than the nominal premium, the health insurer receives the difference in the form of a payment from the risk equalization fund. When the predicted costs are lower, the health insurer is obliged to pay the difference into the risk equalization fund (VWS 2007).

Since the healthcare costs of an individual are predicted and not evaluated ex post, the prediction may differ from the actual (ex post) costs of an individual. When these actual costs are lower, the health insurer profits, and vice versa. If this is the case, the incentive for selection by the health insurer may only be reduced and not removed with the use of a risk equalization model. When certain groups can be identified of whom the predictions systematically differ from the actual costs, risk selection may be profitable for health insurers (Prinsze e.a. 2005; Stam &van de Ven 2007).

Evidence of systematic differences between predicted and revealed costs is shown by Prinsze et al. (2005) and Stam & van de Ven (2007), who indicate predictable losses for almost 40 subgroups. Even with the use of the risk adjustment model, significant losses for these subgroups of a health insurer's portfolio are identified. For example, the predictable loss for insured individuals with more than three diseases is 890 euro and for individuals with stomach problems 3290 euro.

Where the above calculations solely present predictable *losses*, predictable *profits* are identified for a small number of groups (Stam & van de Ven 2007). These groups can be defined as relative healthy[1], but further characterization of these groups has not been done. With this in mind, we want to discuss the rise of two health insurers on the Dutch health insurance market, *Zekur* and *Promovendum*. Zekur is a health insurance of insurer Univé, and their advertising and promotion suggests that they try to attract students as customers. The rise of Zekur even resulted in official questions in the Dutch House of Representatives to the minister of public health, well-being and sports in 2008. Promovendum is an insurer which is active - besides the health insurance market - on several insurer markets and is aimed at higher educated people including students.

Because the lack of research about predictable profits, it is impossible to say whether both health insurers profit from their chosen focus group given the current risk equalization model. Nonetheless, the specific focus groups are in general assumed to be 'healthy' and therefore may be profitable for health insurers (Verweij 2010). This paper addresses this question about selection in an attempt to identify predictable profits for both groups mentioned, students and higher educated individuals.

The main research question in this research therefore is:

Are students and higher educated individuals profitable for health insurers, given the current risk equalization model?

[1] For instance, (1) insured who never have been in the top 25% of healthcare costs (in the preceding five years), (2) insured who never have been hospitalized (in the preceding five years) and (3) insured who self-reported no or just one disease.

The first part of this paper explains the theoretical framework in which this research takes place. In the second part the research method is described. Subsequently, the results will be shown and interpreted. The last part will contain the conclusion and discussion of the results and recommendations for further research.

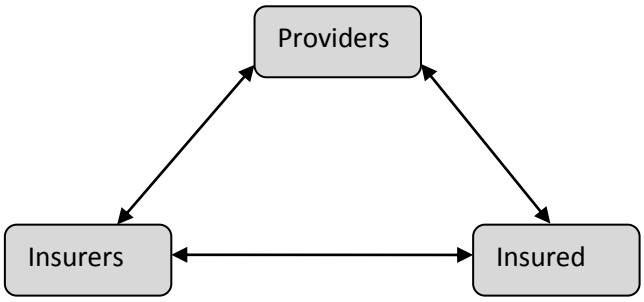
2. Background

In this chapter the background of the study is described. First a description of the present Dutch health insurance market is given. Second, selection is explained and discussed. Subsequently, the risk equalization model is described and additionally the risk adjusters of the 2011 model. And finally the use of education is described.

2.1 Dutch health insurance system

As mentioned, the Dutch government implemented market-oriented healthcare reforms in the social health insurance system in the early 1990s. The Health Insurance Act in 2006 changed the healthcare system, but government regulation in the healthcare sector remained. The introduction of the new healthcare system obliged each person who legally lives or works in the Netherland to buy health insurance. This health insurance contains a legally described benefits package and can be bought from a private insurance company. Due to the changes in 2006, the healthcare market can be divided into three individual markets.

Figure 1: The three markets in healthcare.

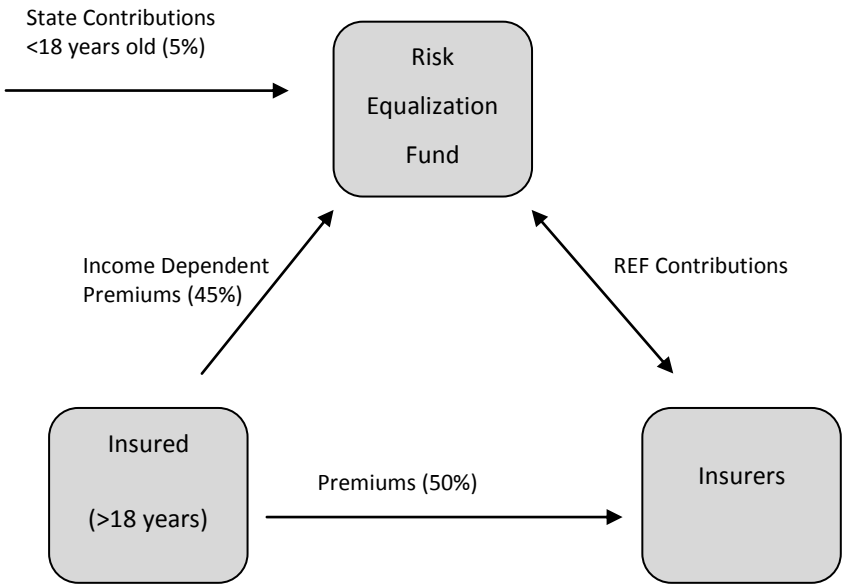


In this paper we will focus on the market between the health insurers and the insured individuals, since the central question lies within that area. This market can be identified as the platform where insurers and insured meet and competition takes place for the product health insurance. For each type of insurance contract which covers the legally described benefit package, a health insurer is obliged to accept each applicant for the same premium per province. Insurers can compete with other insurers to attract individuals with low premiums, high service and other aspects of health insurance.

As already mentioned, to prevent selection the government has implemented a risk equalization model with a Risk Equalization Fund (REF). By adjusting for certain risk factors, the government tries to reduce the incentive for selection by health insurers. In figure 2, an

overview is given of the money flows between the REF, insured and insurers. On average, the insured pay 50% of the insurers' income via the health insurance premium, and 45% via income dependent premiums. For all the under-aged citizens, the state contributes into the REF. The total income of a health insurer depends on the REF contributions, i.e. the composition of the portfolio of the insurer, plus premiums.

Figure 2: Financial flows within the Risk Equalization Fund (REF).



2.2 Selection

The risk equalization fund is implemented to decrease the incentive for selection. These incentives are caused by restrictions on the variation of the premium contributions (van de Ven e.a. 2003). This results in a situation where the premium does not reflect actual healthcare costs and predictable profits or losses arise. Consequence is that health insurers are interested in contracting only individuals with low expected healthcare costs, to ensure they make a profit. In an attempt to decrease this incentive for selection, several adjustment factors are added into a risk adjustment model. By selection we mean:

"Actions[2] by consumers and health insurers to exploit unpriced risk heterogeneity and break pooling arrangements (after Newhouse 1996)"

[2] Not including risk-rated pricing by health insurers.

By definition, both consumers and health insurers are able to perform risk selection. Consumers have more health related information about themselves than the insurer does and therefore can exploit that information-surplus by selecting health insurers and/or insurance coverage. For example, healthy individuals are more likely to choose a deductible than unhealthy individuals (Van Kleef e.a. 2007). Health insurers on their turn can identify several groups for whom predictable profits or losses are present and take measures for both. The introduction of the Health Insurance Act increased the number of tools for health insurers to select, such as more instruments to buy care from caregivers and more flexibility in certain specifications of the benefit package. Although these instruments are not introduced to make selection possible, they can be used for selection. The risk adjustment model adjusts for several variables and subgroups. For every subgroup, the model predicts normalized costs, which represent the costs for this group keeping all other variables equal. These normalized costs are used to predict the total healthcare costs based on the subgroups applicable to an individual. When insurers succeed in only selecting those individuals with lower actual costs than the normalized costs of a subgroup, the predicted costs are systematically higher than the actual costs. For example, the average costs for females in the younger age-groups are partly based on maternal care costs. Selecting females who are not likely to get pregnant may result in predictable profits, since the actual costs are lower than the predicted costs because of the absence of the use of maternal care (Douven & Mannaerts 2008). Calculating the cost difference between females with and without the use of maternal care confirms this[3]. These calculations show that giving birth to a child costs around €7000. When female students are in fact less often pregnant than non-student females in their age-group, their actual costs will be lower, *ceteris paribus*. Another option is to select individuals on characteristics which are present across subgroups. An example is the case of higher educated individuals; their costs may be lower than the normalized costs in all age-groups.

Selection may cause several undesirable outcomes. When predictable profits are large, it is possible that risk selection may be more profitable than improving efficiency. In addition, health insurers have a disincentive to respond to preferences of costumers with predictable losses. Health insurers may give poor services to chronically ill and choose not to contract healthcare providers with good quality of care for treating chronically ill individuals. Selection may therefore threaten quality of care for individuals with predictable losses, i.e. high risks (Prinsze e.a. 2005). In addition, when health insurers are able to attract only individuals with predictable profits, market segmentation is possible. These actions may lead to a segmented

[3] See Appendix 1 for these calculations based on birthrates among females in the relevant age groups and the normalized costs as calculated by the risk equalization model in the Netherlands of 2011

market where individuals with predictable profits are paying a low premium, and individuals with predictable losses are paying a higher premium. In this way selections threatens solidarity. A third possible outcome is a decrease in incentive for health insurers to work efficiently (Van de Ven et al. 2003).

There are different measures to reduce selection. The most effective strategy to reduce selection is good risk adjustment. As already mentioned, the recently used models are not able to fully encounter the problem of selection and therefore other measures may be considered. Allowing for a certain bounded risk rated premium is another option. By allowing for risk rating incentives for selection reduce, because premiums reflect the health risks of an individual to a certain extent. *Risk sharing* is also a possible strategy. Introducing risk sharing means that both government and health insurer bear the financial risk of unexpected healthcare costs. Risk sharing will result in a trade-off between efficiency and selection for the health insurer. Using this strategy efficiency is likely to reduce, since health insurers' incentives for improving efficiency are decreased (van de Ven et al. 2003). In the Netherlands both risk sharing and risk adjustment are used nowadays, but risk sharing is likely to be dropped out the system in the near future.

But is selection really a problem in the Netherlands? One could say that there are predictable losses and profits identified so selection can be profitable, but to what extent will this lead to risk selection? Van de Ven & Schut (2007) present four reasons why the risk equalization system does not need a 'perfect' formula. In the first place, selection is not costless. Risk selection by health insurers has its costs and these costs should be taken into account. These costs can be monetary because the information for selection is not for free, but also in the form of a bad reputation resulting from selection activities. Secondly, by refining the equalization formula the standard deviation of the expected profits and losses will rise. This means that when we improve the formula, there will be more uncertainty whether and to what extent predictable losses or profits actually will arise. Attracting more enrollees is a possible measure to decrease this uncertainty, but this is not for free. A third reason is applicable to small insurers. Even when the equalization formula does not predict the healthcare costs perfectly, one may wonder if small health insurers could obtain accurate information on profitable selection. The fourth reason is that simulation results show that overestimation of the potential selection problem by not ignoring small predictable profits and losses increases when the predictability of the equalization formula rises (Van Barneveld e.a. 2000). They suggest that small predictable losses and profits have to be ignored, because health insurers probably do not benefit from them, since risk selection also brings costs.

These problems with selection decrease the need for perfect risk equalization, but do not encounter the whole problem. The introduction of Health Insurance Act increased both the incentives and availability of tools for risk selection by health insurers (Prinsze e.a. 2005). When predictable profits and losses are just high enough, selection may still be profitable for big health insurers, despite the increasing uncertainty, cost of information and overestimation of the potential selection results. And when we look at the particular case of Zekur, reputation loss is also not a problem. Douven and Mannaerts (2008) argue that Zekur uses self selection by insured rather than taking own measures of selection. Because of the policy conditions, Zekur is not attractive for insured individuals that use a lot of care or did use a lot of care. These groups will not enroll at Zekur in the first place, so using selection measures to get rid of the bad risks is not needed. And when insured do feel limited in the use of health services they have the option to leave Zekur the next day. So when insured actually want to use care, there is a probability that they will switch, which is the ideal case for Zekur and for the insured a nice extra.

2.3 The Risk Equalization model

To make cross-subsidies possible and to reduce incentives for selection, a risk equalization model is used. Cross-subsidies are subsidies between groups, and in the case of the Dutch healthcare system, cross subsidies occur from young to old individuals and from (chronically) healthy to (chronically) ill. With a risk equalization model, the healthcare cost per individual are predicted for the upcoming year. The process for risk-adjusting payments to health insurance can be divided into three steps (Van de Ven & Ellis 2000):

- The risk-adjustment variables have to be identified. A part of this step is to identify factors for which we as society want to subsidize.
- Estimating the relationship between each of these risk-adjustment factors and the costs of healthcare.
- Use these estimated relationships as a basis for determining the risk equalization payments.

In addition to these three steps, several criteria for the identified risk-adjusters should be fulfilled (Epstein & Cumella 1988; Giacomini, Luft and Robinson 1995; van de Ven & Ellis 2000) :

- Validity: they should measure the need for health services utilization and define a system of adjustment in which cells are relatively homogeneous with regard to this need of healthcare.

- Obtainability: they should be obtainable for all potential members without causing problems to the administrative system and without undue expenditures of money or time.
- Invulnerability to manipulation: they should not be subject to manipulation by any group involved.
- No perverse incentives: they should not provide incentives for inefficiency or low quality care.
- They should not conflict with the right of privacy of any group involved.

The risk equalization model we nowadays use in the Netherland contains six risk-adjusters, as presented in table 2.1 (van Vliet e.a. 2009; CVZ 2010; VWS 2007).

Table 2.1. Overview of the nowadays used risk adjusters in the Netherlands.

Risk adjuster	**Description**	**Number of subgroups**
Age * Gender	classification based on age-groups, interacted with gender	20*2 = 40
Pharmaceutical Cost Groups (PCG's)	classification based on previous use of pharmaceutical products	24
Diagnostic Cost Groups (DCG's)	classification based on diagnoses from prior hospitalization	14
Source of income	classification based on the source of income and age	1 + 4*4 = 17
Social-economic status (SES)	classification based on the number of persons per address, the income per address and age	4*3 = 12
Regional clusters	classification based on postal code	10

The age*gender risk adjuster comprises 20 age groups for both males and females. PCG's are groups based on the use of pharmaceutical products in the previous year. These groups indicate the presence of a disease for which medical prescriptions are taken. The groups for

DCG's are based on hospitalizations in the previous year. For PCG's it is possible to be in more than one subgroup. The first subgroup of both cost groups indicates that an individual is in none of the DCG's or PCG's. To be in one or more PCG's, individuals have to use prescribed drugs for several diseases for at least 180 days in the previous year.

Source of income is divided into 5 subgroups of which 4 are combined with age. The first group comprises people younger than 18 or older than 64 years of age. The other groups comprise individuals who are disabled, living from welfare and self-employed. The last group is the reference group and is filled with individuals who are not categorized in the other four groups.

The SES risk adjuster is mainly based on income deciles and divided into three age groups. The first group comprises people who are living with more than 15 persons at the same address. The other three groups are based on a division of income deciles. The first group is in one of the first three deciles, the second group in decile 4 to 7 and the third group in the last three deciles.

The regional clusters are based on several factors. These factors are used to explain that part of the healthcare costs that is not explained by the other risk adjusters. The prediction of this regression is divided into 10 equal groups, giving 10 regional clusters.

2.4 Education and Socioeconomic Health inequalities

The underlying base of this research is the assumption that education causes health inequalities and that the risk equalization model in the Netherlands does not adjust for those health inequalities. The influence of education on health inequalities is mainly measured in research on socioeconomic health inequalities. Socioeconomic status is measured by income, education level and profession and indicates the distribution of knowledge, labour and assets (Mackenbach 1992; Verweij 2010). Socioeconomic health inequalities are defined as systematic inequalities in health and mortality between individuals with a high and low socioeconomic status (Verweij, 2010). Research on socioeconomic health inequalities is frequently done and outcomes are consistent. The life expectation is higher for individuals with a high level of education compared to individuals with a low level of education. In fact, life expectation increases with level of education (Bruggink, 2009). The life expectation at age 65 differs approximately 3 years between the highest and lowest level of education, a difference of more than 15% (CBS 2008). Individuals with a high level of education are less likely to develop certain chronic diseases and live longer in good health than individuals with a low level of education. They live longer without disabilities and rate their health higher than individuals with a low level of education (Kunst, Geurts & Van den Berg, 1995; Kunst 2007; CBS 2009; Mackenbach 1997). Research also shows that these findings are persistent in

Europe over time and between countries, compared to non-Europe countries (Kunst e.a. 2005). In their research in 22 European countries Mackenbach et al. (2008) show that education causes severe inequalities in health and the development of certain cancers and other mortal diseases for both males and females. In addition, results from the *Netherlands Health Interview Survey 1991-1995* show that the number of chronic diseases and overweight increases when the level of education decreases (CBS 1996).

A theoretical base for a relation between education and healthcare consumption is given by Grossman (1972). In a four-quadrant diagram, he relates health production, demand for healthcare and income to each other. This relation is subject to the ability of an individual to profit from healthcare use to increase health. This ability to profit from healthcare is partly based on education. Higher educated individuals are presumed to profit more from healthcare and are more able to know the consequences of unhealthy behavior. By definition of the four-quadrant diagram, both factors increase health. This means that education influences health disregarding income, profession and other factors.

The relation between socioeconomic status and health inequalities can mostly be explained by smoking. Jha et al. (2006) show in their research in England, Wales, Poland and North America, that smoking has the highest influence on socioeconomic health inequalities compared to several other factors. In addition, the fact that the frequency of smoking decreases with higher level of education points in the same direction (Bruggink 2009). Droomers et al. (2005) show that socioeconomic health inequalities related to smoking most significantly are related to the chance of getting addicted to smoking for adolescents. Individuals with a low level of education are also less able to quit smoking. Since smoking decreases health, this seems to be in line with the model of Grossman, where higher educated individuals are presumed to be more aware of the health consequences of their behavior and are more able to act to those consequences.

Research shows existence of socioeconomic health inequalities. The presence of health inequalities related to socioeconomic status does not necessarily mean that students or higher educated are profitable. They are only profitable when the risk equalization model does not adjust for health inequalities related to socioeconomic status. Since income and source of income are included in the equalization formula, the health inequalities caused by those factors are corrected by the equalization model. Education on the other hand, is shown to have a great influence on health and is not included in the equalization formula. This means that differences in education level may be able to identify predictable profits.

3. Data and Methods

This chapter contains the description of the data as well as the methods used in this research. Firstly, the data is described and compared to known statistics of the population of the Netherlands. Secondly, the methods used are described in three parts. In the first part, a model is constructed to measure the healthcare costs of an individual in one year. The second part discusses a risk adjustment model, which is based on the risk adjustment model used in the Netherlands in 2011. Finally, the method is described by which we identify the difference between predicted and realized costs for students and higher educated.

3.1 Data used

The data used for this research is a combination of two surveys. In the Netherlands, every year a main survey is sent out to a representative sample of the non-institutionalized population by the *Statistics Netherlands (CBS)*. This main survey is called *survey on permanent living situation (POLS),* and collects information about gender, age, education, household composition, etc. In addition, the same sample is asked to fill in another, more specific survey. There are three types of these specific surveys: one aimed at health, one aimed at environment and one aimed at law. In this research a combination is used of both the main survey and the survey about health. Yearly data was available from both surveys from 1997 till 2008 (n=129.246). The two surveys were merged using an identifying variable which was present in both. Additionally, the separate yearly datasets where combined into one dataset. This dataset contains demographic variables such as age, gender and income deciles, but also information about health and the use of healthcare. Because many key variables were not continuously collected through the years, only four years of observation could be used in this analysis. The resulting dataset contains observations from 1997 till 2000, with n=40.020. Table 3.1 shows a comparison of certain variables between the dataset and the population, in corresponding years.

To correct for differences between the sample and population, an adjustment factor is added to the data by the CBS. Using this adjustment factor will result in more reliable outcomes, since the sample characteristics are adjusted to those of the population. This adjustment factor comprises age, gender, marital status, urbanization, province and employed. This weighing factor is used in all the subsequent analyses.

As is shown by table 3.1, the mean age in the dataset is lower than in the population. This is caused by the restriction to the non-institutionalized population.

Table 3.1 Overview of the composition of data and population for age, gender and urbanization.

		Year							
		1997		1998		1999		2000	
		Sample	Population	Sample	Population	Sample	Population	Sample	Population
Age	Mean	35,6	37,7	35,4	37,9	35,8	38,0	36,0	38,2
	Mean male	35,2	36,5	34,7	36,6	35,1	36,8	35,3	37,0
	Mean female	36,0	39,0	36,0	39,1	36,5	39,2	36,6	39,4
	<20 (%)	29,1	24,3	30,6	24,3	30,0	24,4	30,3	24,4
	20-40 (%)	30,8	31,4	28,6	31,0	28,0	30,5	27,4	30,0
	40-65 (%)	29,2	30,9	29,5	31,2	30,6	31,6	30,9	32,0
	65-80 (%)	9,2	10,3	9,5	10,3	9,6	10,4	9,5	10,4
	>80 (%)	1,7	3,1	1,7	3,2	1,7	3,1	1,9	3,2
Gender	Male (%)	49,3	49,4	48,8	49,4	49,2	49,4	49,3	49,5
	Female (%)	50,7	50,6	51,2	50,6	50,8	50,6	50,7	50,5
Urbanized	Very strong (%)	17,6	18,2	17,6	18,5	17,6	18,8	17,5	18,9
	Strong (%)	23,6	21,7	23,9	21,7	25,2	21,8	25,7	22,0
	Average (%)	20,7	17,2	20,6	17,4	20,3	17,4	20,6	17,5
	Weak (%)	21,3	20,5	21,9	20,3	21,6	20,1	21,4	19,9
	Not (%)	16,8	22,3	16,0	22,1	15,4	21,8	14,8	21,7

The small difference in mean age between males and females, suggests furthermore that health outcomes may differ less between male and females. In both cases, sample and population, we see a small increase of mean age through the years. When age is divided into groups, the age difference becomes clearer. The sample contains relatively more young and relatively less old respondents than the population, which corresponds with a lower mean age. The consequences of these differences are unclear, but a higher amount of younger individuals suggests better health outcomes. Urbanization shows us an underrepresentation of the outer groups in the sample, and an overrepresentation of the middle groups. The effect of these differences on health outcomes are unclear, since they more or less seem to balance out.

3.2 Calculating healthcare costs

Since the survey does not collect direct information on healthcare costs, these costs have to be calculated. The dataset contains information about the number of drug prescriptions, hospital length of stay and visiting the general practitioner, specialist, dentist and paramedic

caregiver. These variables will be used to calculate the total healthcare costs per person per year. The construction of these costs is shown below.

3.2.1 Costs per visit

To calculate the number of visits to the general practitioner (GP) multiple variables are used. One variable contains the number of visits in the previous two months for the survey. Under the assumption that frequent visitors visit the GP at least one time in the past two months, this variable is multiplied by six, resulting in the number of visits within the previous 12 months. To extract the number of single visits, another method is used. When respondents did not visit the GP in the past two months, the year and the month of their last visit is known. Calculating the difference between the date of survey, and the month and year of their last visit, shows whether they visited the GP in the last year or not. Combining both variables, multiple and single visits, results in a variable which contains the number of visits to the GP. The same method was used to approximate the number of visits to medical specialists and dentists in a year.

In order to translate the volumes in the survey into costs, the mean costs per person are calculated in the population for the GP, medical specialist and dentist. For consistency, costs for 1998, 1999 and 2000 are extracted from a press release of the CBS in 2002. More recent calculated costs are available for those years, but not for every type of healthcare costs used in this research. For 1997, the costs are calculated using the costs of 1998 as a base. The overall increase in healthcare costs in 1998 was 5,8%, from which we can calculate the total healthcare costs in 1997. Because of the lack of better data, the individual costs for GP, specialist and dentist are calculated the same way. Although costs do not seem to behave in this kind of linear way over years, this method is used in an attempt to approach the real cost as close as possible.

By dividing the total costs of visiting the GP, specialist and dentist by population size, the mean costs per person result. When we want to use these costs to calculate the costs per visit, division by the mean number of visits is needed. In order to use these results nowadays, these costs are corrected for inflation and adjusted to 2011 euro's. Table 3.2 shows the results. The mean number of visits seems to be plausible, as the GP has the highest mean and the dentist the lowest. The average number of visits to the GP seems to be constant over time. In 1998, the mean number of visits to the specialist drops with about 0,15 visits. Visiting the dentist has a more up-and-down character, with at most a change of 0,17 visits.

Both the cost per person and per visit for GP and specialist show an increase over the years. This is plausible, since healthcare costs rise over time, even when inflation is taken into

account. The calculated costs for the dentist seem to fluctuate more. The costs per person and per visit seem to rise over time, but this rise is less consistent over the years.

Table 3.2. Overview of the cost calculations for visiting the GP, medical specialist and dentist in 2011 euro's with the use of population size.

		Year			
		1997	1998	1999	2000
	Population	15.567.107	15.654.192	15.760.225	15.863.225
GP	Total costs (x1.000.000)	1.594,38	1.656,19	1.697,88	1.788,61
	Costs per person	102,47	105,80	107,73	112,75
	Mean consults sample	3,82	3,88	3,94	3,84
	Costs per consult	26,83	27,27	27,34	29,36
Specialist	Total costs (x1.000.000)	1.612,40	1.674,04	1.732,81	1.775,23
	Costs per person	102,52	109,20	109,95	112,56
	Mean consults sample	1,94	1,93	1,77	1,72
	Costs per consult	52,85	56,58	62,12	65,44
Dentist	Total costs (x1.000.000)	1.462,58	1.518,49	1.540,69	1.626,89
	Costs per person	93,58	100,00	98,15	102,95
	Mean consults sample	2,54	2,67	2,50	2,65
	Costs per consult	36,84	37,45	39,26	38,85

3.2.2 Costs per hospital day

The survey also collects information about hospital stays. Data is available for at most three stays and per stay the number of days hospitalized is asked, with a minimum of two (one night). Accumulating those three stays, results in a variable which reflects the number of days stayed in a hospital during the past 12 months.

Table 3.3. Overview of the cost calculations for hospital stay in 2011 euro's with the use of population size.

		Year			
		1997	1998	1999	2000
	Population	15.567.107	15.654.192	15.760.225	15.863.225
Hospital stay	Total costs (x1.000.000)	8.468	8.967	9.481	10.066
	Costs per person	707,37	730,33	750,48	771,56
	Mean hospital stay sample	0,51	0,49	0,5	0,48
	Costs per day	1387,00	1490,46	1500,97	1607,41

The costs per hospital night are calculated in quite the same way as in the previous paragraph. First the costs per person in the population are calculated to ensure that these costs are equal between sample and population. To derive the costs per stay in the dataset, these costs per person are divided by the number of hospital days per person in the sample. In this way the mean costs per person are equal in sample and population, but variation by hospital days is possible. The outcomes of these calculations are shown in table 3.3.

3.2.3 Costs of visiting physiotherapist

The costs of visiting the physiotherapist can be derived from the number of visits to the physiotherapist asked in the survey. The original variable is categorized, which means that for calculating the number of visits, the middle of each category is used.

The total costs of visiting the physiotherapist are less clear than the costs used in previous paragraphs. The CBS presents costs for paramedic care in combination with the costs for maternal care. To extract the costs for paramedic care, the percentage of costs accountable for paramedic care has to be derived. This percentage can be calculated by using data from the *Healthcare Insurance Board (CVZ).* This data contains recent cost information of both maternal and paramedic care separately and therefore the factor can be derived. Because the coverage of paramedic care has changed over the years, data is used from 2006, the first year of data collecting for the *Health Insurance Act* (Zvw). In this year, the paramedic costs accounted for 78,09% of the total costs of paramedic and maternal care together. Using this we can calculate the total costs for paramedical care from 1997 till 2000. With these costs we can follow the steps as used in the previous paragraphs, leading to the results as shown in table 3.4.

Table 3.4. Overview of the cost calculations for physiotherapist costs in 2011 euro's with the use of population size.

		Year			
		1997	1998	1999	2000
	Population	15.567.107	15.654.192	15.760.225	15.863.225
Physiotherapist	Total costs (x1.000.000)	751,84	780,58	859,25	873,56
	Costs per person	48,30	49,86	54,52	55,07
	Mean consults sample	2,57	2,74	2,68	3,00
	Costs per consult	18,81	18,22	20,36	18,37

The costs per person seem to rise over time and because of a decrease in the mean number of consults, the mean costs per consult result in a peak. By setting the mean costs per

person equal for the sample and population, a decrease of the number of visits in the sample is likely to create higher costs per visit.

3.2.4 Pharmaceutical costs

Calculating the costs for pharmaceutics is less intuitive than calculating the costs above. The survey collects pharmaceutical information with respect to 24 diseases in the last 12 months. In addition, one question is asked about whether the respondent frequently used prescribed medication in the last 12 months. Because it is impossible to derive the actual pharmaceutical costs for every disease, all costs for the different pharmaceutical treatments are set equal. By counting the number of diseases for which drugs are taken, the total number of different drugs per individual is derived. When the count for all 24 diseases is zero, but the respondent does take frequently prescribed medicines, this count is set to 1.

Using the total costs for pharmaceutical care, we can calculate the costs per person and per prescribed medicine. These results are shown in table 3.5. The costs per medicine are increasing over time, just as the pharmaceutical costs per person. Despite the fact that these costs do not reflect reality because they are calculated for only 24 diseases, these costs are an approximation of actual costs.

Table 3.5. Overview of the cost calculations for pharmaceutical costs in 2011 euro's with the use of population size.

		Year			
		1997	1998	1999	2000
	Population	15.567.107	15.654.192	15.760.225	15.863.225
Pharmaceutical costs	Total costs (x1.000.000)	3.831,4	3.977,9	4.231,6	4.400,4
	Costs per person	246,12	254,11	268,50	277,40
	Mean amount of medication sample	0,73	0,72	0,74	0,71
	Mean costs per medicine	337,16	352,93	362,84	390,70

3.2.5 Overall costs

When we sum all the costs calculated in the previous paragraphs, we get the total healthcare costs per individual. Table 3.6 contains the mean and standard deviation of these six types of costs as well as the mean and standard deviation of the total healthcare costs. Because the total healthcare costs above 120.000 had outliers in every year, these costs are defined missing. Hereby 21 cases were set as missing, in addition to the 63 cases for which no total healthcare costs could be calculated due to missing values. As a consequence, the means in table 3.6 do not correspond exactly with the means as calculated in the previous paragraphs.

Table 3.6. Overview of calculated costs in 2011 euro's for visiting caregivers, hospital stay and pharmaceutical costs

	Mean (€)	Standard deviation	Minimum	Maximum
Type of costs				
General practitioner	107,3	197,7	0	7.399
Medical specialist	107,9	565,9	0	36.898
Dentist	97,7	324,7	0	23.320
Hospital stay	738,3	6.775,6	0	461.055
Physiotherapist	51,9	204,8	0	4.335
Pharmaceutical	261,5	281,1	0	7.411
Overall	1.254,7	4.559,0	0	114.323

As the costs per visit of the GP are lower than those for visiting the medical specialist and dentist, it seems plausible that the maximum values for those two types of healthcare costs are higher than those for visiting the GP. The overall costs have a mean of €1254,7 and a standard deviation of 4559,0. The coefficient of variation is therefore 3,64 where a number between 2,5 and 3,5 seems reasonable. This suggests that the total costs variable has a slightly higher amount of variance than preferable.

The 6 cost components account for 70% of the total costs in the corresponding years. To check whether the total healthcare costs show plausible results, the mean healthcare costs are calculated for five subjective health groups. Under the assumption that a better health results in lower healthcare costs, these calculated costs have to follow this pattern. The results are presented in table3.7.

Table 3.7. Mean costs in 2011 euro's divided into subject health categories

	Share(%)	Mean costs (€)
Subjective Health		
Very good	26,0	530,2
Good	54,5	944,4
Average	11,7	2.384,8
Not bad/not good	5,6	3.102,6
Bad	2,2	6.928,1

As shown in table 3.7 the calculated healthcare costs actually decrease with better health. These results suggest that the calculated healthcare costs are indeed plausible regarding subjective health.

3.3 Risk adjustment model

This paragraph describes the composition of the different variables in the risk adjustment model. The risk adjustment model as used in this research reflects as best as possible the model which is used in the Netherlands, limited by the available data.

3.3.1 Valid cases

Only cases are included in the analysis which contained information for all the risk adjustment variables. When one or more of these variables is missing, the case is excluded from the analyses. In this way 22.055 cases were selected, where the other 17.965 cases contained missing values. In order to check whether these missing values are random or not, further analysis of these missing values will be done. The average healthcare costs for the selected cases are €1053 with a standard deviation of €3865, indicating a coefficient of variation of 3,67.

3.3.2 Age and gender

In the risk adjustment model of the Netherlands 40 groups are composed to adjust for cost differences between age and sex groups. Males and females are divided into groups of five years, with two exceptions. The first age-group of 0-4 years is divided into one for 0 year and one with 1-4 year. The last age-group is set by 90 years or older. The available data from the survey contains variables for both gender and age whereby 38 subgroups could be extracted as shown in table 3.8. Only the oldest age-group for both males and females could not be distinguished in the survey. All subgroups will be included as dummies, except males of age between 50 and 54, they will be used as a reference in the analyses.

The average costs between females and males differ by age. Especially in the two oldest age-groups the average healthcare costs for females are much higher than those for males. As expected, costs seem to rise with age, with the exception that for both males and females the youngest age-group also has high costs. Surprisingly, the costs for males increase over age, but decrease when the age of 80 is reached. The last two subgroups show a decrease in costs. Probably, this is caused by the fact that older individuals receive care from the Exceptional Medical Expenses Act (AWBZ). The oldest age-group for males shows almost an equal number of healthcare costs as males between 55 and 59 years.

Table 3.8. Overview of the composition of the data with respect to gender and age, presented with mean healthcare costs.

	Males (%)	Mean costs (€)	Females (%)	Mean costs (€)
Age				
0	0,7	3.103	0,6	2.845
1-4	3,8	837	3,7	700
5-9	5,0	607	4,8	484
10-14	3,6	188	3,4	507
15-19	1,2	198	1,2	861
20-24	2,9	594	3,5	794
25-29	4,1	586	4,7	1.155
30-34	5,4	630	5,0	1.170
35-39	4,9	648	4,7	1.279
40-44	4,5	848	4,1	1.221
45-49	4,3	828	3,6	1.105
50-54	**3,9**	**1.067**	3,0	1.414
55-59	2,6	1.462	1,8	1.530
60-64	1,8	1.708	1,0	1.852
65-69	1,2	2.700	1,1	2.441
70-74	0,8	2.321	1,0	2.218
75-79	0,6	3.421	0,8	2.642
80-84	0,3	2.742	0,4	5.529
85+	0,1	1.556	0,3	4.218

3.3.3 Pharmaceutical Cost Groups (PCG's)

Since the data contains information about medical use for about 24 diseases, several PCG's could be composed. It is unknown whether respondents used the prescribed drugs for at least 180 days, but composition of PCG's based on these questions is the most accurate data available about pharmaceutical costs in the survey. Table 3.9 shows which PCG's could be extracted and shows the number of persons per PCG per year, where respondents can be in more than one PCG.

The PCG for asthma is by far the largest group. Several groups contain less than 0,5% of the respondents. The results found for these groups are more likely to be statistically insignificant than groups with more respondents like the PCG for asthma. Only 8 of the 23 PCG's used in the risk adjustment model of the Netherlands could be comprised, next to the *no PCG.* As a consequence, less variation in healthcare costs can be explained by using these 8 factors, than the 23 factors in the actual model.

Table 3.9. Overview of the composition of the data with respect to the pharmaceutical cost groups, presented with mean healthcare costs.

		Year				
	Share (%)	1997 (€)	1998 (€)	1999 (€)	2000 (€)	Total (€)
Pharmaceutical Cost Group						
No PCG	89,6	772	850	792	845	812
Asthma	6,2	2.141	1.780	2.656	2.716	2.330
Rheumatism	1,3	3.398	3.025	6.641	3.645	4.096
Epilepsy	0,3	4.447	2.408	6.215	1.296	3.711
Thyroid	0,6	4.702	1.509	2.576	12.306	5.346
Diabetes	1,1	3.117	2.903	4.867	3.862	3.591
Kidney	0,3	2.516	3.768	11.514	2.330	5.369
Cancer	0,3	10.061	8.471	9.084	8.283	9.064
Heart	1,3	7.182	7.587	9.436	9.677	8.439
PCG (mean)*		1,1	1,1	1,1	1,1	1,1
PCG > 0 (%)		10,5	10,1	10	10,7	10,3
PCG = 0 (%)		89,5	89,9	90	89,3	89,6

* Mean calculated for individuals within at least one PCG

As expected, the lowest average costs are found for those who are in none of the PCG's. Despite the fact that the medicines for the different diseases have been assumed to have equal costs, differences in total healthcare costs are present. The highest costs are found for the cancer and heart PCG's, which seems plausible. Nevertheless, the costs for most PCG's fluctuate over time. Especially in the case of the PCG for kidney disease, where the costs in 1999 are up to 5 times higher than in other years. Also the individuals in the PCG for thyroid disease show very fluctuating results. The average costs in 2000 (€12.306) are more than 8 times higher than those in 1998 (€1.509). A further look shows that both the differences for PCG's kidney and thyroid are statistically significant[4]. Looking at the volumes reveals that these differences are probably caused by differences in length of hospital stay. Since the cost per unit is the highest for hospital stay, fluctuations in the length of hospital stay are likely to create big differences. In conclusion, most fluctuations are likely to have a random character, caused by the low number of respondents per PCG per year. Nevertheless, the differences over time for the PCG's kidney and thyroid are probably not caused by random fluctuations but by other factors.

[4] Based on ANOVA test results

3.3.4 Diagnostic Cost Groups (DCG's)

The information for DCG´s has the same source as the PCG´s. As a consequence, less DCG´s could be comprised from the data, because otherwise equal subgroups are present in both PCG's and DCG's. Due to this limited data, only three DCG´s could be composed - next to *no DCG* -, where the original model contains 13 DCG's. Table 3.10 shows the results.

Table 3.10. Overview of the composition of the data with respect to the diagnostic cost groups, presented with mean healthcare costs.

		Year				
	Share(%)	1997(€)	1998(€)	1999(€)	2000(€)	Total (€)
Diagnostic Cost Group						
No DCG	97,6	920	974	943	1.023	963
Arthrosis	1,7	5.066	2.754	5.294	4.169	4.344
Stroke	0,2	5.756	3.946	6.464	2.032	4.854
Stomach	0,6	1.921	5.940	6.875	9.986	5.780
DCG (mean)*		1,6	1,6	1,5	1,5	1,6
DCG > 0 (%)		2,3	2,5	2,4	2,6	2,4
DCG = 0 (%)		97,7	97,5	97,6	97,4	97,6

* Mean calculated for individuals within at least one DCG

The table shows that the DCG arthrosis is the biggest group and the DCG stroke comprises only 0,2% of all respondents. As with the PCG's this may affect the outcomes of the analyses. The pattern for the percentage of people within one or more DCG´s is quite clear. This percentage seems to rise over time. The average costs for people within none of the DCG's are as expected the lowest. As in the previous paragraph, costs seem to fluctuate over time. For the DCG of arthrosis the costs in 1998 are different. Also the average costs for individuals with a stroke have an up-and-down character. The costs for people with stomach diseases seem to rise over time and are the highest of all groups. Tests show that the differences between years for all DCG's are not statistically significant and therefore likely to be caused by random fluctuation, given the small groups.

3.3.5 Source of income

The original risk adjustment variable for source of income has 5 categories, of which 4 are subdivided into 4 age-groups. The first group contains the whole non-labor force: everyone between 0 and 17 years old and everyone older than 65 years. The other four categories are composed with the use of several source of income variables. When we in addition use the four age-groups we get in some cases very small groups. Therefore age is not used to

compose these subgroups and the 5 source of income categories are used as shown in table 3.11.

Table 3.11. Overview of the composition of the data with respect to source of income, presented with mean healthcare costs.

		Year				
	Share(%)	1997(€)	1998(€)	1999(€)	2000(€)	Total (€)
Source of income						
Non-labor force	34,6	1.144	1.053	1.049	1.200	1.114
Disabled	0,2	11.136	1.420	314	1.253	4.039
Welfare	8,1	1.372	1.980	2.006	1.928	1.760
Self-employed	3,6	919	1.375	775	908	984
Reference group	53,6	802	856	1.000	1.007	903

By defining these dummies in the order as presented in the table, respondents cannot be in more than one group. People with disability allowance are the smallest group. The largest group is the reference group, which comprises people who do not fall in the other four categories. Therefore the reference group will be used as the reference when including the dummies in the regression.

Looking at the average costs, the five groups do not seem to differ that much. The only big difference is caused by the very high costs in 1997 for disabled individuals. This difference in costs appears not to be statistical significant[5], indicating a random character of the fluctuation, given the small group size. Individuals living from welfare show the highest costs and the reference group the lowest.

3.3.6 Social economic status (SES)

The original SES variable comprises 4 main categories. Because of lack of data, the first group which indicates whether there live more than 15 persons on an address is not included. The other three groups can be identified and are composed using a variable which indicates the decile of income. The original model divides each of these groups into three age groups, but because of lack of individuals in those groups, only the main SES categories are shown in table 3.12. Costs decrease when SES increases, which seems plausible since income is presumed to affect health, especially low income.

[5] Based on ANOVA test results

Table 3.12. Overview of the composition of the data with respect to social-economic status, presented with mean healthcare costs.

		Year				
	Share(%)	1997(€)	1998(€)	1999(€)	2000(€)	Total (€)
SES Group						
SES1	26,0	1.377	1.594	1.410	1.624	1.493
SES2	40,0	922	812	1038	967	936
SES3	34,0	783	875	815	964	855

3.3.6 Urbanization

In the original risk adjustment model, 10 region clusters are included. These clusters are partly based on the class of urbanization of the city where the respondent lives. With this in mind, urbanization is used as a risk adjustment factor. The urbanization clustering is shown in table 3.13.

Table 3.13. Overview of the composition of the data with respect to type of urbanization, presented with mean healthcare costs.

		Year				
	Share(%)	1997(€)	1998(€)	1999(€)	2000(€)	Total (€)
Urbanized						
Very strong	17,3	855	1.279	1.290	1.270	1.158
Strong	24,8	976	995	1.020	1.078	1.017
Average	20,7	1.047	1.136	974	1.147	1.074
Weak	21,7	1.121	841	984	1.140	1.028
Not	15,4	943	976	1.066	1.041	1.002

The average costs seem quite equal between both different types of urbanization and years. This suggests that type of urbanization may predict total healthcare costs as a whole, but differences between the five types of urbanization are limited. Nevertheless, individuals within very strong urbanized areas have the highest healthcare costs, and individuals in non-urbanized areas the lowest.

3.3.7 Extra Disease Groups

In addition to the original Pharmaceutical and Diagnostic Cost Groups, the data contains information about more diseases than captured in both variables. With the use of the same 24 variables about diseases, 6 extra diseases can be added to the risk adjustment model. Table 3.14. shows the information about those 6 variables.

Table 3.14. Overview of the composition of the data with respect to extra disease groups, presented with mean healthcare costs.

		Year				
	Share (%)	1997(€)	1998(€)	1999(€)	2000(€)	Total (€)
Extra Disease Group						
No EDG	89,0	847	863	846	939	872
Blood pressure	3,7	3.019	2.793	3.066	2.897	2.949
Bowel	1,0	2.950	5.403	4.146	4.569	4.135
Bladder	0,6	2.353	2.770	1.728	1.308	2.014
Migraine	3,5	1.500	1.978	2.152	1.642	1.810
Skin	0,9	1.103	3.618	3.317	1.417	2.401
Back	2,4	3.188	3.564	4.285	4.233	3.818
EDG (mean)		1,11	1,11	1,11	1,11	1,11
EDG > 0 (%)		10,5	10,2	11,4	12,1	11
EDG = 0 (%)		89,5	89,8	88,6	87,9	89

* Mean calculated for individuals within at least one EDG

Looking at table 3.14 we see the percentage of people which are in at least one EDG rise over time. Also in this case some groups have quite a small number of respondents, which may cause insignificant results. Regarding healthcare costs, we see that individuals who are in none of the EDG's have the lowest costs. Bowel and back diseases represent the highest costs, where the EDG bladder has the lowest cost, regarding the EDG's.

3.3.8 Education

To answer the main question of this research, we first have to define both students and higher educated individuals. In this research we use the following definitions for students and higher educated:

"Students are individuals between 18 and 25 years of age, following education on at least *Higher Vocational Education* (HBO) level".

"Higher educated are individuals older than 20 years of age, who completed education on at least *Higher Vocational Education* (HBO) level".

In order to check whether the data of this study shows lower costs for students and higher educated, as indicated by the literature, a comparison is made. Students comprise 3,31% of the sample and 15,60% of the sample is higher educated. Table 3.15 shows the mean costs

per group and their share of the sample. Important is to note that an individual can be in both groups.

Table 3.15. Overview of the composition of the data with respect to both students and higher educated individuals, divided into years and presented with mean healthcare costs.

			Year				
	n	**Share (%)**	1997(€)	1998(€)	1999(€)	2000(€)	Total (€)
Education							
Students	624	37,5	548	592	508	531	544
Non-students	1040	62,5	723	604	1063	666	765
Total age 18-25	1665	100	695	614	829	606	689
Higher educated	3785	25	774	1.120	834	1.006	925
Non-higher educated	11667	75	1.220	1.166	1.336	1.412	1.278
Total age >20	15546	100	1.116	1.151	1.208	1.301	1.189
Overall							1053

The table also shows that both groups have lower healthcare costs compared to respectively non-students and non-higher educated within the same age-group. Without the use of a risk adjustment model, students have €509 lower costs than average (509=1053-544). This means that without the use of a risk adjustment model, students are very attractive to select. For higher educated this difference is €128 (1053-925=128), which means that selecting higher educated may be profitable. When we adjust for age, we see that students differ €145 with non-students in their age-group (689-544=145). A great part of the predicted profit from selecting students disappears when adjusting for age. The difference for higher educated becomes greater when we account for age, namely €264 (1189-925=264). This means that individuals younger than 20 years have lower healthcare costs and accounting for age increases the difference between higher and non-higher educated.

3.4 Applying OLS and comparing means

When we include all the variables of paragraph 3.3 in an Ordinary Least Squares regression of the calculated total costs as presented in paragraph 3.2, we can calculate the so-called normalized costs for each variable in the regression. Since we try to explain the variance of the costs per individual, the betas represent the costs of each subgroup keeping all other variables constant. With these beta's we can predict the costs per individual, based on their characteristics concerning the variables used in the risk adjustment model, using equation 1:

Equation 1: calculating predicted healthcare costs

$$\hat{\gamma} = \sum_{k=1}^{K} \beta_k \chi_k + \varepsilon$$

Where $\hat{\gamma}$ represents the total predicted healthcare costs, χ_k represents the risk adjusters mentioned in paragraph 3.3, with coefficient β_k with k = 1,…,K, and ε represents measurement errors. To calculate whether there are predictable profits or losses for students and higher educated individuals, equation 2 is used:

Equation 2: calculating the difference between predicted and actual costs

$$\gamma^* = \hat{\gamma} - \gamma$$

Where γ^* is representing the profits (if positive), as the result of the total actual healthcare costs γ minus the total predicted healthcare costs $\hat{\gamma}$. To know whether these costs differ significantly, t-tests between predicted ($\hat{\gamma}$) and observed (γ) costs will be performed for both students and higher educated.

4. Results

In this chapter we will show the results of the linear regression on the calculated healthcare costs, using the risk adjustment model as described in the previous section. Subsequently, t-tests will be conducted to test the model and to identify differences between expected and realized costs for both students and higher educated. Furthermore the missing cases will be analyzed as well as the robustness of the models used.

4.1 Regression results

After applying OLS to the calculated costs, the explained variance in the total healthcare costs by the risk adjustment model is 10,7%. As mentioned before, 22.055 cases were included in the regression. This means that over 17.965 cases were not included, which accounts for 45%. The great majority of these missing cases had one or more missing values on the three disease group variables, as well as the social economic status variable. Setting these missing values as value 0 for those groups, caused insignificant results for almost every subgroup in the model so these cases remain excluded.

The regression includes 7 independent variables with in total 68 subgroups. Due to this great number of subgroups, the independent variables will be discussed separately except the disease cost groups, although the results are from the same linear regression.

4.1.1 Gender and age

The results for gender and age are shown in table 4.1. Because the constant is included in the formula, the second column shows the sum of both age-gender and the constant. Since the reference group is males with age between 50 and 54, we have to keep in mind that the coefficients and their significance show values compared to this age group. Choosing this subgroup as a reference results in less significant, but more plausible coefficients in sign and size. As mentioned before, these coefficients represent the normalized costs per subgroup by which we calculate the predicted costs. For males the youngest age-group has the highest costs, which seems appropriate. For females, the two oldest age-groups have the highest costs. This seems to be in line with the fact that females get older, but with a higher burden of disease. As a whole, we see the coefficients are negative or small positive for the youngest age-groups and high positive for the oldest age-groups, for both females and males. This trend is also present in the actual model. Surprisingly, negative coefficients show up in older age-groups of both males and females. This is an unexpected result and probably has a random character, since we see that the coefficients of those groups do not significantly differ from the reference group. In fact, most coefficients do not significantly differ from both the reference group and each other. This means that a lot of age-groups are

expected to have the same healthcare cost, based on this model keeping the other independent variables in the model constant.

Table 4.1. Regression results for age and gender (n=22,055).

		Coefficient	Coefficient + Constant	Standard Error	T-value	Significance (*<0,01;**<0,05)
Constant		422,3		151,7	2,8	*
Gender						
Male (age)	0	2.501,0	2.923,3	325,9	7,8	*
	1-4	151,1	573,3	182,2	0,8	
	5-9	-32,0	390,3	171,3	-0,2	
	10-14	-127,0	295,3	184,6	-0,7	
	15-19	-116,3	305,9	263,1	-0,4	
	20-24	-84,7	337,5	194,8	-0,4	
	25-29	-44,1	378,2	178,6	-0,3	
	30-34	-16,4	405,9	169,5	-0,1	
	35-39	-64,0	358,3	170,9	-0,4	
	40-44	51,8	474,0	173,8	0,3	
	45-49	-87,0	335,3	175,8	-0,5	
	50-54	*Reference*				
	55-59	157,2	579,5	198,1	0,8	
	60-64	-31,3	391,0	233,0	-0,1	
	65-69	1.101,6	1.523,9	264,4	4,2	*
	70-74	406,8	829,1	300,4	1,4	
	75-79	988,1	1.410,4	359,4	2,7	*
	80-84	1.178,7	1.600,9	497,3	2,4	**
	85+	-1,9	420,4	668,8	0,0	
Female (age)	0	2.270,4	2.692,7	344,2	6,6	*
	1-4	27,9	450,2	180,8	0,2	
	5-9	-149,3	273,0	170,0	-0,9	
	10-14	-76,7	345,6	184,5	-0,4	
	15-19	207,8	630,1	258,3	0,8	
	20-24	61,1	483,4	182,8	0,3	
	25-29	426,0	848,3	170,2	2,5	**
	30-34	402,6	824,8	167,9	2,4	**
	35-39	403,7	826,0	169,8	2,4	**
	40-44	325,8	748,1	175,1	1,9	
	45-49	-4,1	418,2	181,3	0,0	
	50-54	240,3	662,6	191,0	1,3	
	55-59	-70,3	352,0	225,4	-0,3	
	60-64	75,0	497,3	288,7	0,3	
	65-69	629,9	1.052,1	271,2	2,3	**
	70-74	634,6	1.056,9	286,4	2,2	**
	75-79	584,8	1.007,1	311,8	1,9	
	80-84	2.988,7	3.411,0	406,1	7,4	*
	85+	2.331,5	2.753,8	513,1	4,5	*

4.1.2 Disease groups

The regression results for the three disease groups are shown in table 4.2. As expected, all the coefficients for both Pharmaceutical and Diagnostic cost groups are significant. Because almost all extra disease groups are significant (except bladder diseases), those diseases seem to be plausible extensions of the risk adjustment model.

Table 4.2. Regression results for the three disease groups.

		Coefficient	Standard Error	T-value	*Significance (*<0,01;**<0,05)*
Pharmaceutical	Asthma	1.083,7	*103,7*	10,5	*
Cost Group	Rheumatism	1.065,1	*236,0*	4,5	*
	Epilepsy	1.524,6	*428,0*	3,6	*
	Thyroid	3.165,0	*326,4*	9,7	*
	Diabetes	810,0	*242,8*	3,3	*
	Kidney	2.905,4	*439,8*	6,6	*
	Cancer	6.269,6	*466,8*	13,4	*
	Heart	5.861,2	*230,9*	25,4	*
Diagnostic	Arthrosis	1.417,7	*210,8*	6,7	*
Cost Group	Stroke	1.566,4	*553,1*	2,8	*
	Stomach	2.940,0	*327,1*	9,0	*
Extra	Blood pressure	536,2	*139,1*	3,9	*
Disease Group	Bowel	1.891,1	*247,3*	7,6	*
	Bladder	-73,4	*311,1*	-0,2	
	Migraine	446,1	*135,5*	3,3	*
	Skin	791,3	*252,8*	3,1	*
	Back	1.722,5	*167,7*	10,3	*

Although these coefficients are sometimes 10 times higher than the normalized costs in the original model of 2011, they do significantly explain the variance of the calculated total healthcare costs. Also in this case, the differences between the coefficients in the original model and the model used in this research do probably differ because of biases in the costs calculation. The relative costs differences are also not in line with the original model. Both cancer and heart cost groups are not the highest cost groups in the original model of 2011, as they are in this model. In contrary, diabetes seems to be one of the higher costs groups in the original model, while is almost the lowest significant group in the model of this study.

These results are probably caused by the assumption that every prescribed drug has the same price, disregarding the type of disease.

4.1.3 Source of income

The results for source of income are less significant. As shown in table 4.3 being self-employed does not significantly explain variance in total healthcare costs. In addition, the regression excludes the non-labor group from the regression, because of multicollineairity. This is probably caused by correlation between age and source of income, since the non-labor group is defined by the age between 0 and 17 or older than 65. Correlation between source of income and social economic status is also an option, since non-workers are presumably in the lowest income deciles. The other two groups are significant. As people who are disabled are likely to need more health care because of their condition, their healthcare costs are probably higher than those living from welfare. Nevertheless, both the relative and absolute difference seems to be too big, surely compared to the differences in the original results of 2011.

Table 4.3. Regression results for source of income

		Coefficient	Standard Error	T-value	Significance (*<0,01;**<0,05)
Source of income	Non-labor	-	-	-	
	Disabled	2.243,3	645,7	3,5	*
	Welfare	376,7	110,8	3,4	*
	Self-employed	103,4	135,5	0,8	
	Reference group	-	-	-	

4.1.4 Urbanization

Also the results for the urbanization subgroups are rather insignificant as shown in table 4.4. The coefficients are the highest in very strongly urbanized areas. This seems plausible, since more urbanized areas are presumed to be unhealthier. Surprisingly, strongly urbanized areas have the lowest coefficients, next to the one of the reference group. Only the coefficients for very strongly urbanized areas are significant, meaning that only living in those areas increases healthcare costs compared to non-urbanized areas.

Table 4.4. Regression results for type of urbanization.

		Coefficient	Standard Error	T-value	Significance (*<0,01;**<0,05)
Urbanized	Very strong	162,9	86,9	1,9	
	Strong	29,2	80,1	0,4	
	Average	131,2	83,0	1,6	
	Weak	68,7	82,1	0,8	
	Not	*Reference*	-	-	

4.1.5 Social-economic status

The results of the social-economic subgroups are shown in table 4.5. We have to keep in mind that the lowest social-economic status group is the reference group and the results have to be compared to that group. The results show a pattern - although not significantly - that higher income is associated with lower healthcare costs. This is in line with the results of the actual model, where the first group has the highest coefficients and the last group the lowest.

Table 4.5. Regression results of social-economic status.

		Coefficient	Standard Error	T-value	Significance (*<0,01;**<0,05)
Social-economic status					
	1. decile 1 to 3	*Reference*	-	-	
	2. decile 4 to 7	22,1	69,8	0,3	
	3. decile 8 to 10	-41,2	71,6	-0,6	

4.2 Identifying the difference

In order to identify the difference between actual and expected costs for the two main groups, t-tests are performed. Based on the characteristics of the respondent, 624 respondents are identified as student and 3875 respondents as higher educated. Of those individuals, 315 are present in both groups. The regression results from the previous section are used to calculate the expected costs for all the available cases. The expected costs for both groups are shown in table 4.6.

Table 4.6. Overview of the expected and actual costs and the difference between both, for students, higher educated and the overall sample, divided by gender.

		Expected (€)	Actual (€)	Difference (€)	Confidence Interval (95%)	Significance (*<0,01;**<0,05)
Group (n)	Students (624)	681	544	137	75;200	*
	Males	596	448	147	68;227	*
	Females	756	627	128	33;224	*
	Higher educated (3875)	952	925	27	-64;199	
	Males	833	799	34	-59;127	
	Females	1.135	1.118	17	-164;199	
	Overall (22055)	1.053	1.053	0		

By definition, the overall difference between the expected and actual cost has to be exactly zero, as indicated in the table. We see that for both groups the expected and actual costs differ positively, which means predictable profits for both groups. The difference is the highest, 137 euro, for the students group (95% CI: 75 - 200) and this difference is statistically significant. The use of the risk adjustment model reduces the difference in costs from €523 (see section 3.3.8) to €137. The difference of €27 (95% CI: -64 - 199) for higher educated individuals is not significant, which means that there are no predictable profits for higher educated found in this analysis. The use of this risk equalization model was able to decrease the cost difference between higher and lower educated individuals with €101 (128 - 27 = 101), and causes the difference to be statistically insignificant

What surprises is the difference between males and females. Based on other research predictable profits were expected to be larger for female than for male students, but in this research the opposite occurs. These expectations were based on the fact that female students are not likely to use maternal care. For students in the survey data, only 2,7% used maternal care in the past 24 months compared to 8,7% for non-students in the same age-group, which is a statistically significant difference. This means that among students 6 percentage points less maternal care use is present. This 6 percentage point difference should cause a cost difference of €420, using the €7000 costs per child as a base[6]. For higher educated these percentages are respectively 11,6% and 11,9%, representing a non-statistically significant difference. When we select only females who did not use maternal care we see that the expected profit for students is almost equal (€130), but the expected

[6] See appendix 1

profit for higher educated is higher (€76), although statistically insignificant. The absence of this difference between male and female students implies that the way we calculated healthcare costs does not reflect the costs for maternal care and the predictable profits for females are underestimated.

4.3 Sensitivity analyses

In order to check whether these results are robust, two additional analyses will be performed. First, subjective health will be added as a regressor in an attempt to check whether students and higher educated rate themselves relative healthy. This was also done by Stam, van Vliet & van de Ven (2010), where they found statistical evidence that subjective health increases the explained variance of a risk adjustment model. Secondly the pharmaceutical costs are taken out of the cost calculating model. Since all medicines have been assigned equal costs, those costs do not reflect the costs per medicines in reality. Excluding these costs from the total healthcare costs calculations may result in more reliable outcomes. The results of the t-test after those changes are presented in table 4.7. The explained variance of the regression increases to 11,6% when subjective health was added (R^2 change p<0,001). Removing the pharmaceutical costs results in a decrease of the explained variance to 4,0%. The combination of both resulted in an explained variance of 4,6%.

Table 4.7. Overview of the results of adding subject health or removing pharmaceutical costs from the model or both for both males and females, on the difference between the actual and expected costs.

		Predicted profit (€)			
		Students		*Higher educated*	
		Males	Females	Males	Females
Sensitivity analysis	None	147*	128*	34	17
	Subjective health added (1)	109**	105**	6	-2
	Pharmaceutical costs removed (2)	157*	121**	34	-10
	Both (1) and (2)	135*	81	-19	11

* = significance < 0,01

** = significance < 0,05

As shown in the table, the predictable profits are still present in two of the three sensitivity analyses. Adding subjective health seems to increase the predictability of costs, but the predictable profit remains significant for both male and female students. Excluding pharmaceutical costs from the healthcare costs decreases the explained variance from the risk adjustment model with 6,7 percentage point. This suggests that pharmaceutical costs are rather included in the total healthcare costs to ensure the predictability of the risk adjustment model. When we exclude pharmaceutical costs from the way we calculate

costs, this results a greater difference between actual and expected costs. Applying both excluding pharmaceutical costs and adding subjective health, results in lower predictable profits than the original model, and creates an insignificant difference for female students between predicted and actual costs. This insignificance is probably caused by the low number of individuals in that subgroup. For almost all the applied sensitivity analyses the predictable profits for males are higher than those for females.

4.4 Missing cases

To verify whether the missing values are random and therefore may influence the results, several t-tests are conducted. In order to identify whether the missing cases contain different values on key variables, comparisons will be made on the following variables: age, gender, subjective health, education and total healthcare costs**.** The means for those variables were calculated for both the whole sample and the selected cases. Then t-tests can reveal any significant differences between those two groups and identify whether the missing cases are random or not. Results for students are presented in table 4.8.

Table 4.8. Comparison of certain variables for students between the whole sample and the selected cases

	Overall	Selected cases	Significance (*<0,01;**<0,05)
Variable			
Gender (females)	50%	53%	
Age (mean)	21,91	22,27	*
Subjective Health (mean)	1,8	1,53	
Healthcare costs (mean)	€ 586	€ 543	

* = significance < 0,01

** = significance < 0,05

These results show that the missing cases for students are quite random. The only statistical significant difference is present for age. The remaining sample is slightly older. This may lead to slightly higher healthcare costs in the remaining sample. Whether this influences the expected profits is unclear.

Differences between the remaining and the original number of cases for higher educated are presented in table 4.9. For higher educated we see more statistically significant differences. All variables differ between the original and the selected sample. The selected cases comprise more females, are younger, rate themselves unhealthier and have lower healthcare costs. This seems to be a contradiction, since less healthy individuals use more care and therefore have higher healthcare costs. The outcomes for higher educated have to be

interpreted carefully, since the healthcare costs are underestimated. The influence of only using those 22.055 cases on predictable profits is nevertheless unclear.

Table 4.9. Comparison of certain variables for higher educated between the whole sample and the selected cases.

	Overall	Selected cases	Significance (*<0,01;**<0,05)
Variable			
Gender (females)	40%	51%	*
Age (mean)	42,69	40,45	*
Subjective Health (mean)	1,89	1,40	*
Healthcare costs (mean)	€ 1.042	€ 925	**

* = significance < 0,01

** = significance < 0,05

5. Conclusion & Discussion

In this chapter the results are discussed and conclusions are drawn. The overall dataset is discussed, as well as the different models used in this research. These outcomes will be linked to the results in an attempt to measure the effect of the methods and data used.

The main question of this research is:

Are students and higher educated individuals profitable for health insurers, given the current risk equalization model?

Results show that selecting students is statistical significant profitable for health insurance while selecting higher educated is not. Students have on average €544 healthcare costs and higher educated €925. Without the use of a risk adjustment model, these averages imply that selecting both groups may result in profits of respectively €503 and €128 per individual. When we compare both groups with their corresponding age-group and therefore adjust healthcare costs for age, we see those differences change to €145 and €264. Only a third of the predictable profit for students remains, when healthcare costs are accounted for age. The predictable profits for higher educated become bigger, indicating that individuals younger than 20 have lower healthcare costs than non-higher educated older than 20.

With the use of the 2011 risk equalization model in the Netherlands, the difference for students between expected and actual costs is €137 and statistically significant. From the original predictable profit of €503, adjusting for age is responsible for a decrease of €399 and the equalization by the other six risk adjusters for €8. We therefore can say that the decrease of the predictable profit for selecting students is mainly caused by adjusting for age. For higher educated, adjusting for age resulted in a predictable profit of €264 instead of the original profit of €128. Using the whole risk equalization model decreased the difference to €27 ($p>0.05$), indicating that health inequalities associated with higher education are taken into account by the risk equalization model.

These profits are higher for males than for female students, which leaves room for questions. Calculations show that female students are likely to be more profitable than male students, *ceteribus paribus*, when these females do not use maternal care. Why this difference is not present in this research is unclear. Most likely is that the cost for maternal care is not reflected in the way we calculated healthcare costs.

5.1 Calculating costs

Translating volumes into costs imposes the presence of both volumes and costs per volume. Since both factors were not clearly present in this research, we tried to approximate both as

best as possible. Furthermore, we used only 6 care-components to calculate healthcare costs, while healthcare costs in the population are a result of many more components. The fact that the calculated healthcare costs do increase when subjective health decreases, shows that these costs do reflect a certain amount of healthcare costs. The use of 6 care-components, representing 70% of the total costs in the population, to calculate healthcare costs means that the actual costs of individuals are probably higher and the model used in this research gives an underestimation of healthcare costs. Differences between both expected and actual costs for both students and higher educated may be higher in reality because of this underestimation.

5.2 Risk equalization model

The dataset did not contain enough information to make a full replica of the original model, but the model used approximated the original model as good as possible. The biggest difference is present in the cost groups. The composition of these groups is quite different from the original model. Less cost groups could be identified and the identified cost groups were not a full copy of the ones in the original model. The lack of cost groups implies that a certain amount of healthcare costs could not be explained and therefore was captured by the other risk factors in the regression plus the error term. Since the missing cost groups are mainly high costs groups which are not likely to be present among students, the model in this research predicts higher costs than the original model should do. This means that both the predicted costs and the predicted profits are overestimated.

In addition, the cost groups have the same base as the pharmaceutical care costs we used to calculate total healthcare costs. This creates a correlation which was indicated by the decrease of the explained variance with a factor 2 when the medical care costs were excluded from the way we calculated the healthcare costs.

5.3 Missing cases

The number of missing cases (17.965) and their significance on several main variables may cause biased results. When missing cases are random, outcomes are not affected by those missing cases, let alone the lower number of respondents. But when missing cases are not random, outcomes may be affected and further research is needed. The selected cases for students are slightly older, although healthcare costs are equal. In the case of higher educated, the selected cases contain statistically significant more females, lower age, lower subjective health and lower healthcare costs.

Surprisingly, the selected cases have a lower health status. The most important difference is indicated by the difference in healthcare costs. The healthcare costs of the selected cases

are lower, which means an underestimation of the actual healthcare costs. The presence of missing cases for higher educated therefore results in an overestimation of the predictable profits for higher educated. But since these predictable profits were statistically insignificant already, the influence of this overestimation is marginal.

5.4 Overall

Despite the fact that the results show that predictable profits per student are 137 euro (95% CI: 75 200, the true value in the population is unknown. Due to the mentioned biases in both the cost calculations and the risk adjustment model only the sign and statistical significance are applicable to the population. The fact that the predictable profits are higher for males than for females indicates that the cost calculating model does not reflect maternal costs for females, and predictable profits for females are underestimated. Calculations of predictable profits for only females without maternal care in the past 24 months, show that only predictable profits for higher educated females are affected by maternal care. Although it was expected that maternal care was reflected in the calculated healthcare costs and the presence of maternal care use for students was lower than for non-students, results show otherwise. The statistically insignificance of the predictable profits for higher educated may be caused by lack of respondents. It is therefore possible that higher educated are profitable for health insurers when the group of individuals is just big enough. Nevertheless, the small size of the difference raises the question whether selecting higher educated finds an empirical base, since selection also brings costs.

The sensitivity analyses show that the results are robust. Applying two types of analyses and a combination of both did not change the results. This suggests that the models used are appropriate and their outcomes are applicable to the population, since the use of different models did not change the results. The fact that students remain profitable even when subjective health is added to the model, indicates that the equalization model in this research is able to adjust for differences in health.

In conclusion, this research reveals an empirical base for health insurer Univé to select students for their health insurance Zekur. Selecting higher educated as in the case of Promovendum, does not find an empirical base in this research.

5.5 Policy implications

The presence of predictable profits means the existence of incentives for selecting students. Looking at the negative side-effects of selection, it is important that the government applies measures to overcome those incentives. Both the use of bounded risk rated premiums and risk sharing may reduce or remove the incentive to select. Since risk sharing is applied nowadays in the Netherlands, the predictable profits found are probably an overestimation of

those in the Dutch population. When the premium reflects the risk of individuals in a certain way, the difference between the premium and actual healthcare costs decreases and predictable profits are less likely to appear.

5.6 Recommendations for further research

This research should be seen as a base for further research for predictable profits and losses based on differences in health state related to education. This research shows evidence for education related differences between predicted and actual healthcare costs, using the risk equalization model of the Netherlands. For further research it is important to improve both the cost calculations and the risk adjustment model. The better the improvement, the better results reflect those of the population. Questionable is the availability of the additional information, since existing surveys probably do not contain this type of information. For further research we would recommend the use of the Risk Adjustment Working Group (WOR) dataset in which the actual costs are known and the whole risk adjustment model in the Netherlands could be estimated. Although privacy-related issues may occur, a combination between WOR-data and the survey data used in this research, gives great opportunities to identify groups with predictable losses or profits.

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Appendix 1

For five age-groups we looked up the number of females and their birthrate in the Dutch population. We also collected information about the normalized costs for the corresponding cost-groups, as calculated by the risk equalization model of 2011. This information is presented in table A1.1.

Table A1.1. Overview of normalized costs, number of children born, and birthrate for females according five age-groups.

	Age	Normalized costs	Number of females	Number of children born	Birthrate
Group					
1	18-25	€1240	613.840	17.990	0,03
2	25-30	€1841	496.343	51.570	0,10
3	30-35	€1973	498.845	69.420	0,14
4	35-40	€1585	589.534	37.213	0,06
5	40-45	€1241	641.028	7.565	0,01

To calculate the difference in healthcare costs for females with maternal care use and the ones without, we use the following equation:

$Y_i = B_r * F_m + (1-B_r) * F_{nm}$

Where Y_i indicates the group number, B_r represents the birthrate and F_m and F_{nm} are the healthcare costs for respectively females with and without maternal care use respectively. The difference between both therefore represents the healthcare costs of giving birth to a child. The composition of the equation shows that two factors are unknown. Therefore we use the same formula for two groups, resulting in two equation with two unknown parameters, F_m and F_{nm} , which can be solved. To ensure the robustness of the outcomes, we calculated the cost for every possible combination of two groups, giving 10 outcomes. To ensure that the difference in costs between two age-groups is not caused by age, we corrected for age by lowering the difference in normalized costs by the difference in normalized costs for males in corresponding age-groups. The outcomes are shown in table A1.2. We see that the average costs of giving birth to a child are €7194 ceteris paribus. Because the calculations used are not exact, the actual costs for the use of maternal care may differ somewhat. Therefore we use the amount of €7000 in this research. This means that a 1% change in birthrate amongst females causes a €70 change in healthcare costs per female.

Table A1.2. Outcomes of the cost calculations for giving birth, as a result of 10 comparisons between the female age-groups in table A1.2.

	Costs for female with maternal care	Costs for female without maternal care	Costs for giving birth
Groups			
1 & 2	€8.632	€1.017	€7.615
2 & 3	€4.281	€1.558	€2.723
3 & 4	€7.113	€1.142	€5.971
4 & 5	€9.289	€1.066	€8.223
1 & 5	€12.995	€885	€12.110
2 & 4	€9.708	€929	€8.779
1 & 3	€7.107	€1.063	€6.044
2 & 5	€8.457	€1.074	€7.383
1 & 4	€7.268	€1.058	€6.210
3 & 5	€7.894	€1.016	€6.878
Mean	8.274	1.081	€7.194