An Empirical Study on Implicit Compensation for Smoking Behavior in the Dutch Risk Equalization Model

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Abbrieviation	Meaning
ASG	Age-sex interacted groups
DCG	Diagnostic cost groups
DemoNorm	Demographically adjusted normative healthcare expenses
DMECG	Dural medical equipment cost groups
GCG	Geriatric cost groups
HCCG	Home care cost groups
MAG	Morbidity-age interacted groups
MHCG	Multiple-year high-cost groups
PCG	Pharmaceutical cost groups
PRS	Profit from risk selection
PTCG	Physiotherapeutic cost groups
REG	Region
SES	Socioeconomic status
SOI	Source of income

Abstract

This empirical study investigates the extent of implicit compensation for smoking behavior by the Dutch risk equalization model and the effects another approach towards lifestyle has on incentives for insurers. Risk equalization aims to keep healthcare accessible for all in a competitive healthcare market by creating cross-subsidies from people with relatively good health to people with relatively bad health. To do so, it provides compensation for predictors of high healthcare expenses. Lifestyle variables, such as smoking, can on the one hand also predict future healthcare expenses, but on the other hand do typically not require compensation because they are the responsibility of the individual. Therefore, risk equalization models do generally not explicitly include lifestyle variables, however, other variables, such as deteriorating health status, often offer implicit compensation. Another approach towards risk equalization, the explicit approach, deals differently with lifestyle variables. They are explicitly included in the predictive model, and afterwards neutralized when calculating normative expenses.

The extent of the implicit compensation of smoking is studied by (re-)creating two risk equalization models: one mimicking the Dutch model of 2016 and one only including the 'fair' predictors of health (age and sex). Both these models calculate normative healthcare expenses for subgroups based on smoking behavior. Four subgroups are defined: never-smokers, ex-smokers, light smokers, and heavy smokers. In a later stage, more potentially 'fair' variables are added to the 'fair' model to validate the results. Finally, the explicit approach will be applied to the Dutch risk equalization system and compared to the conventional approach. It will be examined what this change does to the implicit compensation and incentives for risk selection.

Implicit compensation based on smoking behavior is present in the Dutch risk equalization model. The three smoking groups all have a significantly positive implicit compensation while the never-smokers have a negative implicit compensation (-€117 on average per person per year). This implicit compensation is biggest for heavy smokers (+€382). When more predictors of health expenses, such as source of income and socio-economic status, are added to the 'fair' model, the implicit compensation decreases. Especially the difference in the heavy smoking group is striking (-€19). Ex-smokers are the only group left with a positive implicit compensation. The explicit approach redistributes normative healthcare expenses significantly different compared to the conventional approach. The three smoking groups receive less, and the never-smokers will receive more, leading to less implicit compensation and stronger incentives for risk selection based on lifestyle. The absolute redistribution, however, is only a small fraction of the total amount of implicit compensation.

So, there is implicit compensation based on smoking behavior in the Dutch risk equalization model. A large part of this implicit compensation can be explained through socio-economic and source of income differences between never-smokers and (past) smokers. The explicit approach is potentially favorable over the conventional approach as it eliminates incentives to risk select based on 'fair' variables, decreases implicit compensation, and increases incentives to risk select based on lifestyle variables. There are however assumptions and practical issues that need to be clarified before implementation. For example, it is necessary to know whether insurers can observe lifestyle variables, and if so, which ones. In addition, it should be examined under which circumstances insurers will refrain from risk selection based on lifestyle variables and instead be encouraged to invest in preventive health care.

Chapter 1: Introduction

In recent decades the concept of managed competition in the healthcare sector gained much attention worldwide. With the introduction of this concept efficiency incentives for providers, buyers and consumers of care are created to control the overall healthcare budget. However, when implemented incorrectly, this concept may be a serious threat to the equity, efficiency, and quality of the healthcare system (Enthoven, 1988). To protect these public goals in this vital and sensitive sector, risk equalization has proved to be essential (Van de Ven & Schut, 2007). Risk equalization creates cross-subsidies from people with relatively good health to people with relatively bad health. This ensures that individual health insurance is also affordable for the high-risks with a low-income. One major challenge for risk equalization is how to deal with lifestyle variables that negatively affect health. Is it fair that the financial risks of this type of behavior are borne by the collective? Currently, lifestyle variables, such as smoking, are not explicitly included in risk equalization models. However, implicit compensation for this behavior most likely exists via adjustments for deteriorating health status. This empirical study investigates to what extent the Dutch risk equalization model implicitly compensates for such a lifestyle variable.

The height of risk equalization subsidies differs per individual, based on predictors of future healthcare spending, such as age, sex, and previous diagnoses. The better the included risk factors can predict an individual's healthcare spending, the fewer incentives there are for health insurers to risk select or risk rate. This type of insurer behavior can endanger the quality and the equity of care in a competitive market (McGuire & Van Kleef, 2018). However, it may not be desirable to use every possible risk factor in a risk equalization model to predict one's future healthcare expenditure. Including a variable in the model means that the responsibility for the risk that this variable entails is borne by the collective. When (financial) responsibility for behavior no longer rests with the individual, but with society as a whole, ex ante moral hazard can arise (Ehrlich & Becker, 1972). This change towards more dangerous and less preventive behavior results in increasing healthcare costs for all. Ex ante moral hazard could crowd out caring externalities as citizen's might no longer be willing to pay for rising healthcare costs if they are a consequence of others' health-risk behavior (Van der Star & Van den Berg, 2010). Besides, if health differences originate from lifestyle differences, equity does not by definition require cost compensation for expenditure differences (Schokkaert & Van de Voorde, 2006). Therefore, it is crucial that lifestyle variables are considered carefully in risk equalization models.

Smoking behavior can be considered the single biggest avoidable cause of disability in developed countries and quitting smoking is the single most important thing one can do to improve one's health (Edwards, 2004). So, smoking behavior is clearly a predictor for one's future healthcare spending and is a responsibility of the individual. Given these characteristics, smoking should probably not explicitly be included in risk equalization models. However, other variables, such as the presence of COPD, often offer implicit compensation (Schokkaert & Van de Voorde, 2006). This raises the question whether smoking should only be included indirectly, via deteriorating health status, in the risk equalization model to limit incentives for unwanted insurer behavior (i.e., risk selection) or be dealt with otherwise.

This empirical study focuses on how the Dutch risk equalization model implicitly deals with smoking behavior. The results of this study can give guidance to policymakers who are increasingly struggling with the question of how to control healthcare expenditure while improving the quality and equity of the system. At the same time, the research can also be of added value in the ongoing societal debate in the Netherlands about promoting healthy lifestyles as preventive healthcare (Ministerie van Volksgezondheid, Welzijn en Sport, 2018a).

The aim of this empirical study is to map out the relationship that the Dutch risk equalization model holds towards smoking behavior. Specifically, it is studied to what extent implicit compensation is present for smoking behavior. After, the consequences of this possible implicit compensation are discussed and alternative ways of dealing with smoking behavior regarding risk equalization are explored. The exact research question reads: To what extent does the current Dutch risk equalization model implicitly compensate for smoking, and what are the consequences of this?

This research question will be answered on the basis of various sub-questions. These sub questions are:

- What is the rationale of risk equalization?
- How can risk equalization models deal with lifestyle variables?
- Which of the risk adjusters in the Dutch risk equalization model are (causally) correlated with smoking?
- Does the current Dutch risk equalization model implicitly compensate for smoking behavior?
- What are the consequences of this possible implicit way of dealing with smoking?
- What are the consequences of alternative ways of dealing with smoking?

The rationale of risk equalization, the structure of the Dutch Healthcare system and different methods on how to deal with risk adjusters in risk equalization will be discussed in the Theoretical Framework. In the Methods section, a description of the data sets, study strategy and simulation models will be provided. Thereafter, the Result section will display the findings from the performed analyses. In the end, the Discussion part will provide a critical assessment of the study. The main findings and their implications will be reviewed in context to the existing literature and strengths and weaknesses of this study will be assessed.

Chapter 2: Theoretical Framework

To answer the research question, not only specific information about individual's predicted and actual healthcare spending and smoking behavior is needed, but also a conceptual framework should be drafted. This framework discusses the rationale for risk equalization, defines compensation- and responsibility-variables, describes different ways in which models may deal with C- and R-variables and explains the Dutch health insurance system.

2.1: The Rationale for Risk Equalization

2.1.1: The Foundations of Risk Equalization

Before examining how risk equalization functions, the legal, moral, and historical foundations of regulated competition and risk equalization are considered.

From a legal perspective, there has been increasing international attention for the right to health. After the Second World War, the United Nations took a leading role in protecting human rights, including the right to health. The right to health is laid down in the international covenant on Economic, Social and Cultural Rights article 12 as: *"The States Parties to the present Covenant recognize the right of everybody to the enjoyment of the highest attainable standard of physical and mental health"* (den Exter, 2009). As explained in General Comment no. 14, financial accessibility to healthcare is part of this right to health. This General Comment further specifies that states party to the covenant must ensure an equitable distribution of all health facilities, goods, and services. Equitable distribution in healthcare is often explained as a distribution of care according to the need of care. Others have defined equity in healthcare as the absence of systematic disparities in health and in the major social determinants of health between groups with different levels of underlying social advantage/disadvantage (Braveman & Gruskin, 2003). Besides, states also have the obligation to ensure that privatization of the health sector does not constitute a threat to the (financial) accessibility of health, according to the General Comment (den Exter, 2009). This legal framework, as provided by international health law, presents states an important, and difficult, task to make and keep healthcare accessible and equitable.

These legal foundations are derived from the growing moral understanding in western democracies that access to healthcare and education are key to creating equal chances for all. Most societies strive for equality in opportunity as complete equality is not possible and maybe even undesirable. Equal opportunities to access healthcare comes with the moral realization that the economically self-sufficient must help those who are unable to maintain decent living standards on their own. What the decent health minimum is, depends heavily on the wealth and technology available in each society. Enthoven (1988) believes that all care "that equates marginal benefits and marginal costs for people of average incomes in that society" and "can effectively prevent or cure disease, relieve suffering and correct dysfunction" should be available for all. This moral understanding presents societies an essential, and tough, duty.

To do justice to these legal and moral obligations, governments have developed national health insurance plans. Health insurance is appropriately understood as social insurance and not casualty insurance. That means that its goal is not merely to protect individuals against unexpected variations in their own medical expenditures, but it also protects all members against uninsurable risks, such as the birth with a genetic predisposition to disease. Social insurance assures universal financial access to the decent minimum and requires cross-subsidies from the well to the sick (Enthoven, 1988).

Over time, these national insurance plans increasingly struggled with rising costs and inefficiencies. Growing wealth, advancements in technology and aging of the population, drove faster expanding healthcare costs compared to gross domestic products (GDP). In 1970, 6.9% of the GDP in the U.S. was spent toward total health spending (both through public and private funds). By 1995, the amount spent on healthcare had increased to 14.1% of the GDP (Kamal, McDermott, Ramirez & Cox, 2020). In the Netherlands a quite similar pattern can be identified. In 1970, 5.9% of the GDP was spent on healthcare and by 1995, this number had increased to 8.8% of the GDP (Huber, 1999). So, health spending growth outpaced economic growth in the 1970s and '80s, and this started to weigh heavily on the budget.

In an attempt to control the rise in healthcare costs, countries started to adopt capitation and coinsurance policies. These policies, however, resulted in conflicts concerning the right to health, inefficiencies due to government failure and, thus, eventually healthcare costs were not contained (Cutler, 2002). Responding to this, policymakers made more often room for competition in the healthcare sector. Competition among (private) insurers and providers of care aim to create incentives for efficient allocation of resources (Enthoven, 1988). However, to keep healthcare equitable in a competitive market, regulation, such as risk equalization, is essential.

So, from an economic-historic perspective there is a call for more efficiency, and thus competition, in healthcare. Combining this with the moral, and legal, calling for equity and accessibility, requires regulations of this very competition.

2.1.2: Unregulated Competition in the Healthcare Market

Competition among insurers of care potentially has positive efficiency effects but can on the other hand also have negative effects on the affordability and equitability of care. Competition needs to be regulated to minimize, or preferable eliminate, these negative effects and maximize the positive effects.

An unregulated competitive health insurance market is incompatible with social health insurance. Due to the so-called equivalence principle, it is impossible to create essential cross-subsidies without government interference. The equivalence principle entails that health insurers tend to minimize profit on every single health insurance contract, by cause of competition. Health insurers can achieve this through either risk selection or risk rating. This type of behavior in this unregulated competitive health insurance market will result that healthcare is no longer distributed according to need but based on ability-to-pay and on predictors of good health, such as a young age or well-educated status.

Risk rating means adjusting the premium of a contract based on the expected claims under that contract. Ultimately, this will lead to a situation in which everyone is charged with a different price, based on their risk. Consumers with high risks of becoming ill, are charged with a higher premium compared to consumers with a low risk. An extreme, luckily fictitious, example based on the Dutch healthcare system, demonstrates that pulmonary arterial hypertension patients will be charged with a forty times higher premium compared to patients with no medical conditions, if risk rating were to be allowed and performed by insurers (McGuire & Van Kleef, 2018). These excessive differences in premium are, of course, a threat to equitable (financial) access to care. For that reason, possibilities for risk rating by insurers are largely regulated. Community rating, where insurers are required to offer every consumer a health insurance for the same price regardless of health status, is the most used solution.

Because risk rating is often incomplete, due to information asymmetries and uncertainties, unregulated markets also tend towards risk selection (Field, 1993). Risk selection means adjusting the risk profiles of the consumers group based on the premium of that contract.

Risk selection can take numerous forms, but the most striking form is rejecting applicants, with a high risk, from insurance. This form is in no way compatible with equitable access to care and therefore prohibited by many regulators: insurers often are obliged to accept all eligible applicants. Consumers can also risk select themselves. This happens when low-risk individuals choose not to insure because it is not financially attractive for them. It leaves competitive insurers with no other option than to raise the premiums or have (extreme) negative profits. Therefore, in most regulated systems consumers are obliged to insure themselves with a health insurer. A third form of risk selection concerns the action of insurers to make their health plans more attractive for the low-risks and less attractive for high risks. This can result in worse quality care for chronic, high-risk patients (Van de Ven, Van Kleef & Van Vliet, 2015). So, risk selection can be a serious threat to the equitability, affordability, and quality of the system. There are solutions, but those do not eliminate risk selection completely.

So, collective action is required to make healthcare affordable for the high-risks and bring equity into the system. A regulator will be needed who sets the rules of the game. One major regulation-tool such a sponsor has, to bring about equity and reduce incentives for risk rating and risk selection, is risk equalization.

2.1.3: Risk Equalization in Practice

Risk equalization enables social insurance in a competitive health insurance market. It aims to maintain the essential cross-subsidies from people with relatively good health to people with relatively bad health in this competitive market. It will remove insurer incentives for risk selection and risk rating by collecting premiums into an equalization-pool. The subsidies from this pool are redistributed over health insurers based on the risk profiles of their customers.

Risk equalization is a specific type of risk-adjusted subsidy where the subsidy is not given to the consumer, but to the insurer for lowering transaction costs. All counties that apply risk-adjusted subsidies give the subsidy to the insurer. In a transparent competitive market, insurers are forced to reduce each consumer's premium by the personalized subsidy they receive for this consumer. By giving risk-adjusted subsidies to the insurers, the different risks consumers represent for the insurers are equalized. This is the essence of risk equalization (Preker, Lindner, Chernichovsky & Schellekens, 2013).

Health-cost-predictors such as age, sex, prior medication, and previous diagnoses determine the height of the risk-adjusted premium subsidies. The more accurate risk adjusters can estimate future health expenditure, the better the incentives for risk rating and risk selecting are limited. Perfect risk equalization would eliminate all incentives for risk selection and risk rating. However, as predicting future health expenses for all individuals is very complex, risk equalization is generally incomplete and therefore combined with other regulations that limit risk selection and risk rating, such as the earlier discussed community-rating, obligations to accept applicants and to be insured (Preker, et al., 2013)

There are two common modalities for risk equalization. In modality A, the consumer pays (part of) the contribution directly to the risk equalization fund (REF). In modality B, the consumer pays the contribution to the REF via the insurer (see Figure 1). Modality B has an advantage over modality A that it generates lower public expenses, as the contribution is paid to a private insurer. An advantage of modality A is the higher premium sensitivity, due to larger relative differences in premiums between insurers, which stimulates competition. Another advantage of modality A is that it provides the opportunity to make subsidies income-related, which enables to create cross-subsidies from higher to lower incomes (Van de Ven, 2007).

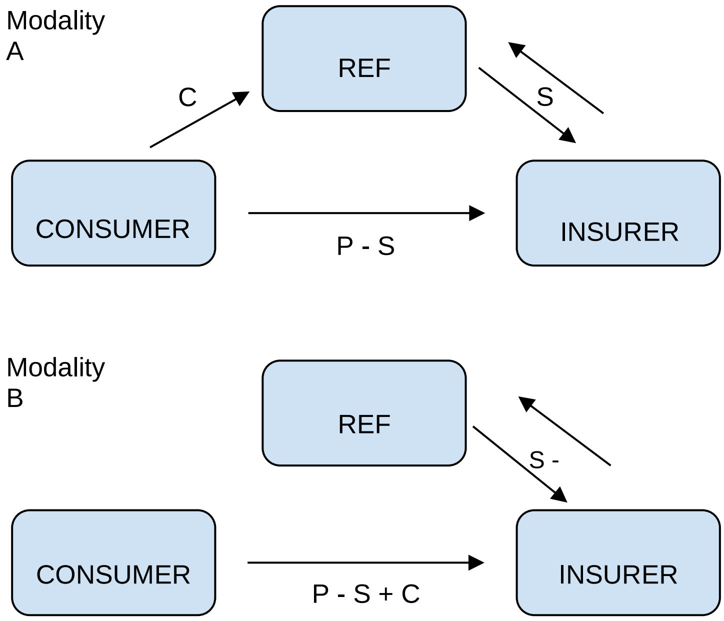

Figure 1. Modalities for risk equalization; P = premium, S = subsidy, C = contribution

2.1.4: Risk Adjusters

The height of the premium subsidy, on an individual level, is determined by risk adjusters. Risk adjusters are variables that contain personal information. This information has predictive value for future healthcare expenses. On the one hand, these risk adjusters need to be able to predict future health expenses as accurately as possible, to limit incentives for risk selection by insurers. On the other hand, not all predictors for future health expenses might be as desirable to be used in risk equalization because including a variable in the model means that the responsibility for the risk that this variable entails is borne by the collective. Risk adjusters can commonly be classified into two groups: C(compensation)-variables and R(responsibility)-variables.

C-variables, or legitimate risk adjusters, are variables on which compensation is desirable. The risks that these predictors entail should generally be borne by the collective. This is because the individual can in no way be held responsible for these risks. The most striking example of a compensation-variable is age. Including C-variables in a risk equalization model is key for creating cross-subsidies, and thus essential for creating equal financial access to care.

R-variables, or illegitimate risk adjusters, are variables on which compensation is rather undesirable. Schokkaert and van de Voorde (2006) mention three of these so-called undesirable R-variables. First, it is explained why lifestyle variables can be considered as R-variables. Financial risks that arise from lifestyle choices are regarded as the patient's own responsibility and therefore there is no ground for compensation. Second, variables that are directly linked to healthcare provider or insurer behavior should not be included in risk equalization formulas. Differences in these variables reflect differences in efficiency of insurers. Compensation for these variables could kill incentives for efficiency, the main goal of introducing managed competition in healthcare. A third subtype of R-variables concerns variables that might create incentives for manipulation or upcoding by healthcare providers or insurers when they are included in the risk equalization formula.

McGuire and van Kleef (2018) indicate eight types of risk adjusters that potentially can be used for risk adjustment. The demographic risk adjusters age and sex are named ‘classics’ and are included in every risk equalization model. Usually, the terms age and sex are interacted and a 1- to 5-year increment is used for defining age groups. As discussed, earlier age and sex are the most prominent examples of C-variables because the health risks posed by these characteristics are independent of own actions.

A second type of risk adjuster is diagnostic information on patients from previous hospital visits. Diagnoses are used as risk adjusters in risk equalization models of e.g., the US, Belgium, the Netherlands, Israel, and Germany. This risk adjuster has quite impressive results regarding predictive value; the R-squared for demographic-diagnoses-based models is 0.41 compared to 0.015 for age-sex alone in US commercial data. One downside of this risk adjuster is the risk of incentives for upcoding, especially when providers and insurers vertically integrate (Geruso & Layton, 2020). Besides, certain diseases for which compensation will be offered do not originate ‘at random’. These diseases may originate partly due to the behavior of the patients. Therefore, such diagnostic information can be considered an R-variable.

A third risk adjuster is pharmacy information. This risk adjuster is currently used in Germany and the Netherlands. An advantage of this risk adjuster is that drug use can often signal chronic conditions that are being controlled by medications and which will be missed when only diagnoses are used for predictions. Disadvantages are the potential incentives for providers to stimulate overuse of drugs among patients and the possible interaction between lifestyle and drugs prescription. So, also this risk adjuster has both its advantages and disadvantages.

The fourth risk adjuster discussed is information about the prior-year spending. Now only the Netherlands uses a form of this risk adjuster. The predictive value is promising; the R-squared can be up to 0.21. However, using this can also create incentives for overproduction of healthcare in year t-1, to receive more compensation in the year after. This problem is largely overcome by the Dutch form of using prior-year spending information. The Dutch model includes dummy variables based on risk classes for people with very high spending in multiple prior years. It is shown that these dummy variables have additional predictive value in a system where also diagnoses and pharmacy information is already included (Van Kleef & Van Vliet, 2012). Prior-year spending information by type of service rather than total spending improves this predictive value even more (Ellis & McGuire, 2007; Ellis, Jiang & Kuo, 2013). This information is also included in the Dutch model of 2016, high spending for home care, physio therapeutic care and geriatric rehabilitation. When including variables of prior-year spending, it must be considered that these high expenses are not generated completely randomly, but sometimes find their origin in structural unhealthy behavior. The classification of this risk adjuster as either C- or R-variable is still open for discussion.

A fifth risk adjuster is prior healthcare utilization information. Only the Netherlands and Switzerland include this type of information in their model. Both countries use a dummy variable based on respectively durable medical equipment and hospital use in the prior year. Cost-containment incentives may be hampered by this risk adjuster, while improving predictive value. What the balance is of these two opposite effects, remains to be investigated (McGuire & Van Kleef, 2018).

The sixth risk adjuster discussed, medical record information, is still unused in risk equalization. Information from medical records, such as test results, doctor’s interpretation, and suspected diagnoses, might have additional predictive value, but obstacles are momentarily in the way. Medical records are, in the US, often insufficiently standardized and rather incomplete, due to privacy issues. Incentives for manipulation are also an issue here (McGuire & Van Kleef, 2018).

Self-reported measures, such as health surveys, is another group of risk adjuster that is still unused. This group has long been a good candidate to be used, however high costs and (un)representative responses have been the main obstructions for implementation. Because the required survey information is not available for the entire population, direct use of self-reported health measures as risk adjusters is problematic. Collecting this information for the entire population would usually be considered too cumbersome and costly (Van de Ven & Ellis, 2000). However, the welfare loss, through more serious risk selection, by not including these variables may outweigh these costs (Schokkaert & Van de Voorde, 2004). Self-reported measures can on the other hand have added value in Constrained Regression (CR-)models, instead of the Ordinary Least Square (OLS-)method currently used for estimating risk equalization models. The use of health survey information in risk equalization through CR can be promising in reducing incentives for selection via plan design for groups not explicitly flagged by other risk adjuster variables (Withagen-Koster, Van Kleef & Eijkenaar, 2020). This type of risk adjuster may also include information about lifestyle.

The last type of risk adjuster indicated is socio-economic variables. This entails variables such as income, occupation, race, and region. These variables are quite commonly used in Europe. Although this type of risk factor does not generally lead to substantial increases in R-squared, including them in a predictive model can redistribute large amounts of money; from plans with relatively many self-employed to plans with many unemployed for example. Differences in social-economic status do not directly affect future health expenses. It is potentially mediated by health literacy (Stormacq, Van den Broucke & Wosinski, 2019). It remains a political question whether people with lower income should be compensated for that.

The great variety of risk adjuster types have now been discussed. Policymakers are faced with many options on variables to include and which not. It is too simply to say that only C-variables, or that all possible risk adjusters, should be included. First, because it is largely an ethical and political question whether a variable requires compensation for or not. Second, because including too little variables can lead to serious threats of affordability and quality of care through incentives for risk rating and risk selection by health insurers. Including too many variables on the other hand can create or maintain incentives for manipulation, upcoding and unhealthy behavior.

2.1.5: The Conventional and Explicit Approach

This section will focus on the different ways to cope with lifestyle variables in risk equalization. After the first ethical and political question has been answered (indicating C- and R-variables), another question arises; how should these C- and R-variables be treated differently in risk equalization?

Not treating these different variables differently, so including them both in the risk equalization model, is rather atypical. The predictive value of the model is likely to rise, however, at the expense of risks for manipulation, moral hazard, and unfairness. This problem might be overcome (partly), when the contribution to the risk equalization fund is made lifestyle-dependent for the lifestyle variables taken up in the model. This contribution should then be distributed over the insurers according to the lifestyle profiles of their consumers. In that case, individuals with an unhealthy lifestyle are faced with financial incentives to stop their unhealthy lifestyle, and will contribute more, partly solving the problem of moral hazard and unfairness.

To answer the question above, it is important to define the function of a risk equalization model. According to Schokkaert and Van de Voorde (2004), a strict distinction should be made between two functions: (1) explaining medical expenditures, and (2) formulating normative payments. They argue that, to meet both these goals, both C- and R-variables should be incorporated in the risk equalization formula. When predicting future medical expenses, all possibly predicting risk adjusters should be included in the formula to prevent omitted-variables bias. So, this also includes lifestyle variables such as smoking behavior. However, when calculating the subsidies, the effects of the R-variables should be neutralized by putting them at their mean value. This approach is known as the explicit approach and differs from the more commonly used conventional approach, where R-variables are simply omitted (Schokkaert & Van de Voorde, 2006).

Theoretically, the explicit approach transfers the risks exposed by R-variables from the community to the private insurer. The explicit approach can have two possible effects on insurer behavior. Insurers will try to risk select, or even risk rate, based on the R-variable, depending on what the regulator allows. In this case, the risks exposed by the lifestyle choice is passed on to the individual. This entails for example that insurers will try to attract consumers with a healthy lifestyle or charge higher premiums for people who smoke, drink or practice dangerous sports. This type of behavior by insurers will create financial incentives for individuals to change their lifestyle. These financial incentives have shown to be successful in stimulating people to quit smoking (Volpp et al., 2009). However, as explained earlier, risk selection and risk rating may form a threat to the accessibility and quality of care and will (to a certain extent) be regulated by governments. When risk selection is impossible or insufficient, insurers may set up a general campaign to promote a healthy lifestyle among its consumers. In that way not the premium is increased to make a profit, but it is attempted to lower the actual (future) healthcare expenses of consumers. Incentivizing insurers and individuals to promote a healthy lifestyle is very much in line with the call for more preventive healthcare in the Netherlands (Ministerie van Volksgezondheid, Welzijn en Sport, 2018a).

Simply not including R-variables in a risk equalization model, as happens in the conventional approach, can have major consequences for the equity of the healthcare system. It can lead to incentives for risk selection, not only based on R-variables but also based on C-variables; that one thing that risk equalization aims to eliminate. Schokkaert and Van de Voorde (2006) show that omitting R-variables from the model can lead to implicit compensation of R-variables, such as lifestyle variables. The effects of the omitted R-variables are partly taken up by other, presumable compensation-, variables. This can bring about a problem, but only when the R- and C-variables are not distributed independently in the population; for instance, when there is a correlation between smoking behavior and age. Let's assume that both a higher age and smoking lead to higher healthcare expenses and that there is a negative correlation between these two variables, i.e., there are relatively more smokers among the young, than among the old. The difference in compensation between the old and the young will then decrease, as a larger part of the expenditure effect of smoking is taken up by the young than by the old. If insurers can then differentiate based on smoking behavior, they will see that the young are more attractive than the old *within* the group of non-smokers and *within* the group of smokers. In other words, when insurers are capable to extract the expenditure effect of the R-variable, while the model does not change, they will be able to risk select based on a C-variable. In this case, it makes the young more attractive to insurers, so there are incentives for risk selection based on a C-variable (and an R-variable: smoking). This is due to the so-called omitted-variable bias. Thus, the conventional risk equalization approach creates, or at least fails to remove, incentives for risk selection based on C-variables. Premium differentiation based on characteristics for which the individual is not responsible is precisely one of the problems that risk equalization aims to overcome.

This statement, however, comes with an assumption that insurers can indeed differentiate their risks based on R-variables, i.e., they can observe the lifestyle variables of their consumers. Because if this is not the case, the explicit model will generate incentives for risk selection/risk rating based on C-variables and the conventional model will not. So, when using the explicit model only information that is available to the insurer should be included (Schokkaert & Van de Voorde, 2006).

To conclude, policymakers are faced with three different options on how to deal with lifestyle variables in risk equalization. The first, rather atypical, approach is to fully include lifestyle variables in the risk equalization formula. This means that the compensation will be partly determined by the behavior of the individual and the financial risks this behavior entails will not directly be borne by the individual, or in this case the insurer. The second option concerns the conventional approach, where lifestyle variables, and other R-variables, are omitted from the formula. No explicit representation can, however, lead to implicit compensation and incentives for risk selection based on C-variables. The third option is the explicit approach, as explained by Schokkaert and Van De Voorde (2004, 2006). This model creates incentives for risk selection/rating based on lifestyle variables under certain circumstances.

2.2: The Dutch Health Insurance System

The following section will provide an overview of the Dutch health insurance system. This system sets the framework wherein this study will be conducted.

The philosophical basis of the Dutch healthcare system are the following more or less universal principles: equal access to healthcare for everyone, solidarity through health insurance and top-quality healthcare services (National Health Care Institute, 2021). Although not explicitly mentioned by the National Health Care Institute, cost-containment and efficiency can also be seen as pillars on which the current Dutch healthcare system is built.

The Dutch health insurance system consists of three layers. Layer 1 concerns the Long-term Care Act, which regulates a mandatory public insurance for long-term care, such as care provided in nursing homes (McGuire & Van Kleef, 2018).

The second layer regards the Health Insurance Act, which was newly introduced in 2006. This private health insurance scheme covers the costs of prescribed drugs, mental care, home care, rehabilitation care, hospital care and physician services. This part of the system finds its origins in managed competition (Van de Ven & Schut, 2008). Private insurers, who fully bear financial risk, are incentivized to compete with each other on price and quality of care to attract as many consumers as possible. Competition among the insurers aims to create efficiency in the healthcare market. Government implemented six regulations of this competition to achieve individual affordability and accessibility. (1) Income-related allowances are provided for low- and middle-income families. (2) The benefit package of care is standardized by the Minister of Health and (3) insurers are obliged to offer this package with community-rated premiums. The rate of the standard care package is determined by the individual insurers. These regulations eliminate risk rating completely. (4) Being insured by a private insurer is mandatory and (5) open enrollment regulates the obligation to be accepted by insurers. (6) The risk equalization fund redistributes risk-adjusted subsidies among insurers. These regulations aim to minimize incentives for risk selection. Another regulation, a mandatory deductible, intends to stimulate cost-conscious behavior among consumers. The consumers can, besides choosing between the competing insurers, also choose the level of an extra voluntary deductible and the type of insurance contract: restitution or natura (McGuire & Van Kleef 2018).

The third layer of the Dutch insurance system deals with Supplementary Health Insurance. Enrollment is on a voluntary basis. Competing private health insurers, who fully bear the financial risk, offer supplementary packages of care, for example dental care and physiotherapy (McGuire & Van Kleef, 2018).

The first layer was projected to cost €18 billion in 2017, which makes up 2.6% of the Dutch GDP. The second layer makes up 6.1% of the GDP with about €43 billion of spending projected. The third layer will cost €4 billion, about 0.5% GDP (Tweede Kamer, 2017).

The rest of this theoretical framework will focus on the second layer of the Dutch health insurance system and more specifically on the risk equalization model.

2.3: The Dutch Risk Equalization Model

The Dutch risk equalization fund (REF) is the hearth of the risk equalization model. The REF is under control of the National Health Care Institute, an independent administration body. It takes a neutral position between the Ministry of Health, Wellbeing, and Sport and health insurers. The Netherlands has a model comparable to modality A, where the consumer pays its contribution, which is income-related, directly to the REF. Contributions for individuals under 18 years old are paid by the government. The REF redistributes these contributions over the insurers based on risk adjusters. A complete overview of the payment system is provided in Figure 2.

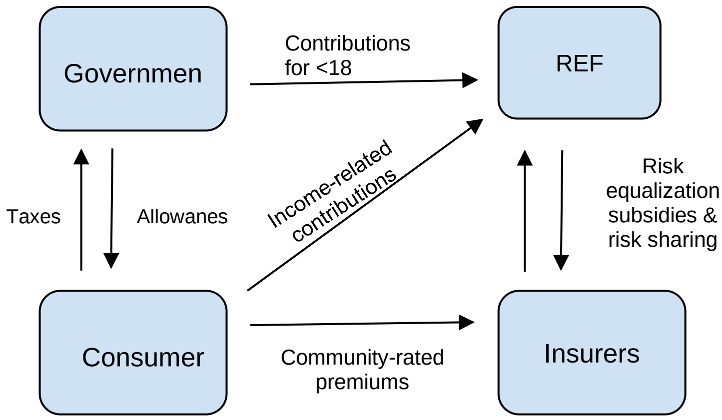

Figure 2. Financing Scheme of the Health Insurance Act (McGuire and van Kleef, 2018)

The risk equalization system includes four different risk equalization models for different types of care: somatic healthcare, short-term mental care, long-term mental care, and out-of-pocket payments due to the mandatory deductible. The focus of this study is solely on the first model: the model for somatic healthcare expenses.

The risk equalization for somatic care is almost completely ex-ante. Ex-ante means that the contribution that the insurer receives from the risk adjustment is determined before the calendar year to which the contribution relates. So, the insurer bears full responsibility for shocks occurring during the year to which the contribution relates. In 2017, ex-post compensations were almost entirely abolished to stimulate efficiency. Ex-post compensations used to take place when estimated and realized costs for insurers differed significantly, and these differences were not within the influence of the insurer. The only exemption from this are newly included treatments for which no data are available yet (Ministerie van Volksgezondheid, Welzijn en Sport, 2018b).

The Dutch risk equalization model for somatic care is based upon 12 risk adjusters which form 162 dummy variables together, with new variables being added almost every year.

A complete overview of all dummy variables of the 2016 risk equalization model is included in Appendix A. The following twelve risk adjusters form the 2016 model: age interacted with sex (ASG), pharmaceutical-based cost groups (PCG), diagnosis-based cost groups (DCG), multiple-year high-cost groups (MHCG), durable medical equipment cost groups (DMECG), yes/no morbidity in interaction with age (MAG), source of income interacted with age (SOI), social economic status interacted with age (SES), zip-code clusters (REG), and high-cost groups for home, geriatric and physio therapeutic care (HCCG, GCG, PTCG) (National Health Care Institute, 2015b).

The coefficients for these dummy variables for the year *t* are from a regression of medical spending in year *t-3,* or even before if the definition of the risk adjuster requires so. The estimation method to determine the coefficient is OLS-regression. The spending data from *t-3* is first made representative for the year *t* and covers the entire population. All individuals are also weighted with the fraction of the calendar year they are enrolled. The R-squared of the risk equalization model for somatic care is 0.31 in 2017 (McGuire & Van Kleef, 2018).

The risk equalization payment for the insurer is equal to the predicted spending for somatic care (plus the predicted spending for long- and short-term mental care and OOP-spending), minus a fixed amount. This fixed amount is determined by the government and equals about 50% of average personal spending. As there is no difference between the model for predicted spending and calculating the payment, the conventional approach, as explained above, is in place in the Netherlands.

McGuire and van Kleef (2018) indicate five ongoing issues regarding the Dutch equalization model. The first challenge concerns the overcompensation for low-risk individuals and undercompensation for high risks. This incentivizes insurers to risk select. Selective advertising for low-risks individuals and quality skimping for high risks are the most prominent examples of potential risk selection in the Netherlands (Van de Ven, et al. 2015). The Dutch Healthcare Authority investigated (the possibilities for) risk selection and concluded that momentarily there are no problems, although there might be in the near future. The indicated options for risk selection include group contracting, offering almost identical supplementary health plans for different prices, the voluntary deductible and premiums targeted to switchers (Dutch Healthcare Authority, 2016).

Some other challenges for the Dutch risk equalization system are the increased incentives for upcoding when more risk adjusters added, the introduction and complexity of risk equalization for long-term care, and the difficulty of measuring the absence of risk selection, as the actions that can be regarded as risk selection are unlimited.

A final challenge indicated by McGuire and van Kleef (2018), concerns the topic of this study. For some types of spending variation, the regulator might not want cross-subsidies, such as lifestyle differences that lead to spending variation. Not including these R-variables, as is current practice, theoretically leads to implicit compensation. This study investigates to what extent there is implicit compensation for smoking behavior. McGuire and Van Kleef (2018) illustrate two options for regulators to deal with this unwanted implicit compensation. Either correct observed spending for effects of R-variables, or the explicit model should be introduced, and insurers should be given the possibility to risk rate their health plan premiums based on these R-variables.

To conclude, the Dutch Risk Equalization model is very extensive. Research is currently mainly focused on improving the predictive value of the model, with the goal to limit undercompensation for high-risk individuals. With the inclusion of more long-term care in the system of managed competition, this objective has become even more important. Perfect risk equalization, which is essentially impossible, has not been achieved, despite the inclusion of many risk adjusters in recent years. So, incentives for risk selection are still present, albeit difficult to measure to what extent. The newly included risk adjusters possibly introduce incentives for upcoding and may increase implicit compensation of R-variables.

Chapter 3: Research Methods

In this section, the research strategy of this quantitative, empirical study will be discussed. First a description of the available datasets is given. These datasets form the basis of the study. Second, the main research groups will be indicated and defined. Third, the method for studying the possible correlation between the individual risk adjusters of the Dutch risk equalization model and smoking behavior will be explained. Fourth, the method of indicating implicit compensation of R-variables in a risk equalization is considered. Fifth, and final, the technique used for applying the explicit approach on the Dutch risk equalization system will be examined.

3.1: Datasets

To investigate the presence of implicit compensation for smoking behavior in the Dutch risk equalization system, information about two subjects is essential: information about smoking behavior among the Dutch population and information about the compensation payments per Dutch individual. This information has already been collected and resides at the Dutch Central Bureau of Statistics (CBS).

The first dataset is the Dutch Health Monitor of 2012. The Dutch Health Monitor is a questionnaire that is administered every four years and maps the health and lifestyle of the Dutch population (Rijksinstituut voor Volksgezondheid en Milieu, 2021). The data collection is largely performed by the municipal health services (GGD's) and partly by the CBS (376,384 and 10,811 respondents respectively) (Centraal Bureau voor de Statistiek, 2015). The 2012 questionnaire was chosen because this questionnaire makes a distinction on how many cigarettes people smoke. The, more recent, 2016 questionnaire does not contain questions on the number of cigarettes. The 2020 monitor results are not yet available at the time of writing.

The second dataset contains administrative information on healthcare costs and risk adjusters used in the current Dutch risk equalization model. For each individual, it is known which risk adjusters are present, what the total healthcare costs have been and what the risk equalization payment was. This data is collected by the National Health Care Institute. For this study, the 2016 risk equalization model will be used. This is because the coefficients of the dummy variables for 2016 follow from a regression on medical spending in 2013 (t-3). Along with the fact that smoking behavior from 2012 is viewed as a possible predictor for medical spending in the future, i.e., in 2013.

These two datasets are linked anonymously. So, it is possible to combine information on smoking and healthcare costs for every single individual. The linked datasets contain the data of approximately 400,000 respondents. Due to a weighting factor the information about this group can be extrapolated to the entire Dutch population of 2013, with a minimum age of 19 years old (11,975,777 persons). This weighting factor, for instance, considers the overrepresentation of older respondents in the dataset due to oversampling. The respondents with missing data on smoking behavior or the weighting factor will be excluded from the study.

3.2: Research Groups

To investigate the presence and extent of implicit compensation on smoking behavior in the Dutch risk equalization system, the cases will be subdivided into four groups. These groups are mutually exclusive, so a respondent can only be in one of the groups.

The first group is the 'never-smoker' group (S_N). This is the group of people who answered in the negative on the following two questions: *'Do you ever smoke?'* and *'Have you smoked in the past?'*. The second group is the 'ex-smoker' group (S_E). This includes the respondents who answered that they currently do not smoke but have smoked in the past. The third group, ‘light smokers’, contains the people who do smoke at the moment of the questionnaire, however less than 20 cigarettes a day (S_L). These cigarettes can either be from a package or self-rolled. The final group includes the respondents who smoke 20 cigarettes or more per day. This is the ‘heavy smoker’ group (S_H). This cut-off value corresponds with the cut-off value used in research by the Trimbos Institute, an independent research institute on lifestyle, mental and youth care (Trimbos, 2019). S_E, S_L, and S_H together will be referred to as the smoking groups.

The advantage of creating four subgroups, instead of two main groups (smokers vs. non-smokers), is that the degree of smoking and history of smoking is also weighted in the results. It is likely that smokers are forced to stop smoking due to deteriorating health status. This group can in this case be distinct from the never-smokers. Besides, it allows analyzing the difference in implicit compensation between people who smoke occasionally and people who are heavily addicted to smoking.

3.3: Demonstrating Correlation

The analysis of the data is performed using the software package SPSS statistics. The first step of this analysis is the exploration of a possible correlation between risk adjusters and smoking behavior. As explained in the theoretical framework *(section 2.1.5)*, the conventional approach of risk equalization can lead to implicit compensation of R-variables if there is such a correlation between C- and R-variables. In this case the illegitimate risk adjuster is smoking behavior, and the legitimate variables are pure C-risk adjusters that are included in the Dutch risk equalization model, such as age and sex. The distribution of C-variables will be presented for each of the four research groups. A significant discrepancy of this distribution between the four research groups indicates the presence of a correlation. For categorical variables, a chi-squared test will be performed and for an interval variable a one-way ANOVA or Kruskal-Wallis test (dependent on the variable having a normal distribution) will be used. This correlation can either be negative or positive. There is a negative correlation between smoking behavior and the risk adjusters if there are less (ex-)smokers among the people with (cost-increasing) risk adjusters. They are positively correlated if there are more (ex-)smokers among the people with (cost-increasing) risk adjusters.

Besides, in this step, it is explored whether there is a correlation between smoking behavior and other risk adjusters. Are smokers and ex-smokers more often diagnosed with certain diseases? Some risk adjusters, such as pharmaceutical or diagnostic cost groups, are regarded as C-variables. These variables are after all included in the risk equalization model. The correlation between smoking behavior and the variables DCG, PCG, MHCG and DMECG is explored using chi-squared tests.

In addition, it is examined whether there is a statistically significant relationship between smoking behavior and healthcare expenses. Does smoking on average lead to higher healthcare costs? A multiple regression will be performed with healthcare expenses as dependent variable and smoking behavior as independent. Other risk adjusters, such as age, are added as independent variables to control for confounding as much as possible.

3.4: Indicating Implicit Compensation

The second step of the analysis is indicating the presence of implicit compensation of R-variables and, if present, the extent of this compensation. This will be achieved by comparing two variables over the four defined research groups: (1) normative healthcare expenses and (2) compensation payment based on pure C-variables.

The normative healthcare expenses equal the predicted healthcare costs of that person. This prediction follows from the Dutch risk equalization model of 2016. The model is mimicked by performing an OLS-regression. Almost all risk adjusters are included as independent, dummy, variables with the actual healthcare expenses over the whole year 2013 as dependent variable. In total 145 risk adjusters are added, those applicable to individuals under 18 years old are not included. This results in the following formula:

1) Conventional: $E_i = \varepsilon_0 + \alpha_1 * x_{1i} + \alpha_2 * x_{2i} + \cdots + \alpha_k * x_{ki} + \mu_i$

where E_i is the actual expenditure of individual i, ε_0 is the coefficient of the reference group to be estimated, α are the coefficients of risk adjusters to be estimated, x {0,1} are dummy variables of risk adjusters and μ_i is a disturbance term. The estimated coefficients that resulted from this regression are used to calculate the normative healthcare expenses. This formula is used:

2) Conventional: $N_i = e_0 + a_1 * x_{1i} + a_2 * x_{2i} + \cdots + a_k * x_{ki}$

where N_i is the normative healthcare expenses of individual i, e_o is the estimated value of the reference group, and a are the estimated values of the coefficients of risk adjusters.

The expenses calculated with this model can differ slightly from the real normative payments due to three factors. First, because the dependent variable may be different due to the removal of cases with missing data. Second, because in the original model minor restrictions are set for simplification of implementation practice. These restrictions apply to the PCG's, where one individual can be subdivided in multiple groups. However, this should not lead to significant differences (Ministerie van Volksgezondheid, Welzijn en Sport, 2015). Third, because the datasets used in this study do not contain information for Dutch citizens with an age under 19 years old.

Next to the normative expenses a second cost variable is considered, namely the 'fair' compensation based on only C-variables. This compensation originates from the average actual healthcare expenses per age-sex group. In the remainder of this study, this variable will be named 'demographically adjusted normative healthcare expenses' (DemoNorm). This is a basic model for determining the compensation, with only two C-variables included. These two variables (age and sex) are the purest C-variables. However, as discussed in the theoretical framework, the qualification of a risk adjuster as C- or R-variable is arbitrary. Therefore, a sensitivity analysis will be performed with more variables included in the results.

Differences between the actual and normative heath expenses within the subgroups indicate that there are incentives for risk selection based on smoking behavior. If the actual health expenses for certain subgroups in the population are lower than the normative health expenses, this creates a potential profit from risk selection (PRS) for the health insurer. As discussed earlier, incentives for risk selection can threaten the quality and (financial) accessibility of care, even if it is based on a lifestyle variable.

The normative healthcare expenses and DemoNorm will be compared for each subgroup. If the DemoNorm is smaller than the normative healthcare expenses in the smoking groups, implicit compensation is present. If the two variables are equal in the different groups, implicit compensation is not present. A paired t-test will be used to indicate significance.

For the sensitivity analysis, three extra risk adjusters will be included separately: social-economic status (SES), source of income (SOI) and region (REG). These variables, together with the age-sex (ASG) dummy variables, are separately used as independent variables in multivariable OLS-regression analyses, with actual healthcare expenses as the dependent variable. One extra OLS-regression will be performed using ASG, SES, SOI and REG as independent variables. The calculated coefficients are used to compute a predictive model and compensation will be formulated for the four research groups. In this model all variables will be regarded as legitimate risk adjusters, so the conventional approach is followed.

3.5: Applying the Explicit Approach

The last part of the analysis is applying the explicit approach to risk equalization on the Dutch model. Theoretically, the conventional approach can lead to incentives for risk selection based on C-variables, as is shown by Schokkaert and van de Voorde (2006). They demonstrate that the explicit model overcomes this problem. It will be examined to what extent the explicit approach will distribute the risk-adjusted compensations differently, compared to the conventional approach.

First, the Dutch risk equalization model of 2016 will be mimicked. This will be done in the same manner as described above *(section 3.4)*. Second, the explicit approach will be applied on the Dutch system. To do so, three dummy variables (ex-smoker (yes/no), light smoker (yes/no) and heavy smoker (yes/no) are added to the linear regression analysis. The dummy for never-smokers is not added, and it will function as a reference group. The addition of these three dummy variables will improve the predictive value of the model and therefore more accurately predict future healthcare expenses. This results in the following equation:

3) Explicit: $E_i = \varepsilon_0 + \beta_1 * x_{1i} + \beta_2 * x_{2i} + \cdots + \beta_k * x_{ki} + \gamma_1 * x_{k+1i} + \gamma_2 * x_{k+2i} + \gamma_3 * x_{k+3i} + \mu_1$

where E_i is the actual expenditure of individual i, ε_0 is the coefficient of the reference group to be estimated, β are the coefficients of the risk adjusters to be estimated, x {0,1} are dummy variables of risk adjusters, γ are the coefficients of the smoking dummies to be estimated and μ_i is a disturbance term.

When calculating the risk-adjusted contributions the three new dummy variables are fixed to their respective population means. This results in the following formula for calculating the normative health expenses:

4) Explicit: $N_i = e_0 + b_1 * x_{1i} + b_2 * x_{2i} + \cdots + b_k * x_{ki} + g_1 * p_{R1} + g_2 * p_{R2} + g_3 * p_{R3}$

where is the normative healthcare expenditure of individual i, e_o is the estimated value of the reference group, *b* are the estimated values of the coefficients of the risk adjusters and x {0,1} are dummy variables of a risk adjusters, g are the estimated values of the coefficients of the smoking dummies and P_{R1}, P_{R2}, P_{R3} are the probabilities of the smoking groups in the entire population.

The normative expenses that follow from the explicit approach will be compared with the normative expenses that resulted from the conventional approach. For all individuals the two will be subtracted, and the difference will be demonstrated. First this will be done for each individual sample. After, a similar evaluation will be performed but with the population split based on smoking behavior. The difference between the two will be tested using a paired t-test.

Chapter 4: Results

In this chapter the results of the analyses will be presented in four sections. First, the overall dataset will be viewed and the characteristics of the four subgroups will be shown. Second, the correlations between smoking behavior and the risk adjusters of the 2016 Dutch risk equalization model will be displayed. Third, the (possible) implicit compensation is presented, including a sensitivity analysis. Last, the results of the explicit approach are demonstrated.

4.1: Subgroup Characteristics

The two datasets, the Dutch Health Monitor 2012, and the dataset with information on 2013-costs and risk adjusters from the risk equalization model 2016, were first linked anonymously. In total the two data sets combined contained 387,195 cases. After the removal of missing cases for smoking behavior and weighting factor, 357,030 cases were left. In the remainder of the analyses, a weighting factor will be taken into account to make the data representative for the entire Dutch adult population (19+). This makes the data represent 11,975,777 people.

The characteristics of the four research groups are presented in Table 1. The largest group is the S_N-group, ten times bigger than the smallest group: the S_H-group. The S_E are the oldest, having a more than ten-year gap with the youngest group, the S_L. The highest proportion of females can be found within the S_N-group with 56.93% compared to the S_H of which only 39.22% are female. The highest mean health expenses are found in the S_E-group. The expenses of this group are on average almost €1100 more compared to S_N. As indicated are all the differences between the groups are statistically significant. The following significance tests are performed: mean age (Kruskal Wallis, followed by pairwise Mann-Whitney), sex (Chi-squared), mean health expenses (Kruskal Wallis followed by pairwise Mann-Whitney), frequencies (Chi-squared), and number of cigarettes (Kruskal Wallis followed by pairwise Mann-Whitney).

Subgroup	Never-smoker (S_N)	Ex-smoker (S_E)	Light smoker (S_L)	Heavy smoker (S_H)
Age; years	45.8 **	55.83 **	44.7 **	46.5 **
Female; %	57.0% **	47.8% **	44.6% **	39.2% **
Mean health expenses over 2013; €	€2,005.08 **	€3,101.75 **	€2,076.33 **	€2,634.03 **
Frequency; % (weighted)	5,187,373 (43.3%)	3,985,012 (33.3%)	2,262,569 (18.9%)	540,823 (4.5%)
Frequency; % (unweighted)	145,500 (40.8%)	143,866 (40.3%)	54,834 (15.4%)	12,830 (3.6%)
Mean number of cigarettes a day	0	0	8.3 **	23.3 **

Table 1. Subgroup characteristics (**; p-value <0.01)

The statistically significant differences in age and sex between the subgroups make it difficult to compare them on their mean health expenses. Both age and sex have a strong correlation with health expenses. Younger individuals tend to have lower health expenses on average and the same holds for male individuals as compared to females (see the coefficients of ASG in Appendix A). Therefore, age and sex can be classified as confounders. However, the observation that S_L have higher mean health expenses compared to S_N, despite the lower proportion of females and lower mean age, is then even more striking.

The difference in mean health expenses between S_E and S_N is noticeable, however so is the difference in age. Not much can be said about this at first sight because this difference may partly or fully originate from a difference in age and may have nothing to do with smoking behavior.

So, the differences in age and sex make it difficult to compare the subgroups on mean health expenditure at first glance. However, age and sex do not pose a difficulty when comparing the subgroups on normative health expenses or implicit compensation. This is because both these C-variables are taken into account when calculating both the normative expenses and the DemoNorm expenses.

4.2: Correlation Smoking and Risk Adjusters

In this part of the results the correlation between smoking behavior and the great variety of risk adjusters is demonstrated. For each risk adjuster of the Dutch risk equalization model of 2016, except for the age/sex dummies, the weighted and relative frequency is measured. This is measured for all four subgroups independently. In Appendix B a complete overview of these results is provided. Here a summary is presented and only some, the more striking, results will be analyzed.

The regression coefficients, following from the OLS-regression analysis with the conventional approach, are used to indicate which risk adjusters are significant and cost-increasing. These coefficients can be found in Appendix A. The p-values of nearly all risk adjusters were significant ($p<0.05$). The frequencies of the positive (cost-increasing) and significant dummies are summed per risk adjuster and subgroup and shown in Table 2. For example, the coefficients of the SES variables 1, 4, 5, 7, 8, 10 & 13 are both positive and significant. These are mainly groups with a lower income. The exact definitions can be found in Appendix A. The frequencies of these variables are summed per subgroup. So, 59.3% of the S_N-group are tagged with cost-increasing SES dummies and the other 40.7% are in the reference group, tagged with cost-decreasing SES dummies or tagged with insignificant cost-increasing SES dummies.

The age/sex dummies are replaced in these results by two more easily interpretable dummies: age 65+ (yes/no) and female (yes/no). The coefficients of the risk adjuster dummies age 65+ and female are both positive and significant, following from a separate OLS-regression which is not shown in the results.

Risk adjuster	**Significant cost-increasing dummy**	**Never-smoker (S_N)**	**Ex-smoker (S_E)**	**Light smoker (S_L)**	**Heavy smoker (S_H)**
Age	65 + years	16.0%	28.8%	10.1%	8.3%
Sex	Female	56.9%	47.8%	44.6%	39.2%
Region	Not living in the reference region	89.5%	90.2%	90.4%	91.0%
SOI	(partly) disabled for work or receiving social security beneficiaries	9.4%	8.6%	14.0%	25.3%
SES	Mainly lower income groups	59.3%	50.5%	69.8%	76.2%

MHCG	High healthcare costs in previous years	5.3%	9.8%	5.2%	7.4%
DMECG	Using catheters or steaming aids	0.7%	1.4%	0.6%	0.6%
DCG	Diagnosed with a disease	8.9%	15.7%	9.1%	10.7%
GCG	High costs in geriatric care in previous years	0.2%	0.3%	0.1%	0.2%
PTCG	High costs in physio therapeutic care in previous years	2.2%	3.3%	1.8%	1.8%
HCCG	High costs in home care in previous years	2.4%	3.1%	1.4%	1.8%
PCG	All PCG except psychosis, Alzheimer's, addiction, transplantations, and cancer	21.9%	40.5%	24.4%	37.6%

Table 2. Frequency of cost increasing risk adjuster dummies per subgroup

First, the S_N and S_H groups will be compared. The most prominent difference between the groups is seen in the dummies for source of income (SOI). S_H are around 16%-point more likely to be classified with a cost-increasing dummy compared to S_N. Around one on four heavy smokers is (partly) disabled to work or receive social security beneficiaries, compared to approximately one in ten never-smokers. For SES dummies also a difference of 16%-point can be identified. This indicates that lower incomes are more common among S_H compared to S_N. Another difference is seen in multiple-year high-cost (MHCG), where S_H are more likely to have (extreme) high health expenses in the past. A last major difference is seen in the PCG dummies. S_H are almost 16%-point more likely to receive prescribed medication for cost-increasing medical conditions compared to S_N.

The second comparison will be made between the S_N and S_L. For SOI and SES dummies a similar type of difference as described above, albeit smaller, can be seen. These differences are respectively 5% and 10%. Another difference is seen in HCCG. Here S_N are more likely to make high costs in home care compared to S_L. This difference, however, might very well originate from a difference is age (see difference in 65+ age).

The third comparison is made between the S_N and S_E. Here. also a difference can be seen in the SOI and SES dummies, however one in the opposite direction. Now, lower income and being (partly) disabled or receiving social security beneficiaries is less common among the S_E compared to the S_N. In the MHCG, DMECG, DCG, HCCG, PTCG and PCG, the combined frequencies of cost-increasing dummies are substantially higher for the S_E compared to the S_N. In the MHCG, DMECG and PCG it is even twice more likely that a S_E is tagged with cost-increasing characteristics than a S_N. These are serious differences but can besides the difference in smoking history also be explained by the age difference between the two groups.

The results in GCG and PTCG follow the same trend as MHCG and DMECG. However, the percentages for these risk adjusters are minimal, and so drawing firm conclusions requires some caution, despite the significance of the results. The correlation between smoking and sex is negative, as S_N are more likely to be female compared to all smoking groups.

Now, with a little more detail, the correlation between smoking and PCG will be presented. Within each of the 31 PCG dummies the frequencies of the subgroups is demonstrated. This is presented in Figure 3. For example, within PCG_0 46.4% did never smoke, 29.8% is an ex-smoker, 19.8% is a light smoker and 4.1% is a heavy smoker. These percentages can be used as some sort of base, as they apply to the group of Dutch adults who are not receiving medication for any of the diagnosis applicable in PCG_1 to PCG_30.

The first observation is that in 29 of the 30 PCG's the frequency of S_N is lower than our base group (PCG_0). Or in other words, the smoking groups are more prevalent in almost all medication groups compared to individuals who do not receive medication. Only PCG_28 shows a slightly higher percentage of S_N. PCG_28 resembles the presence of a very rare disease (pulmonary arterial hypertension).

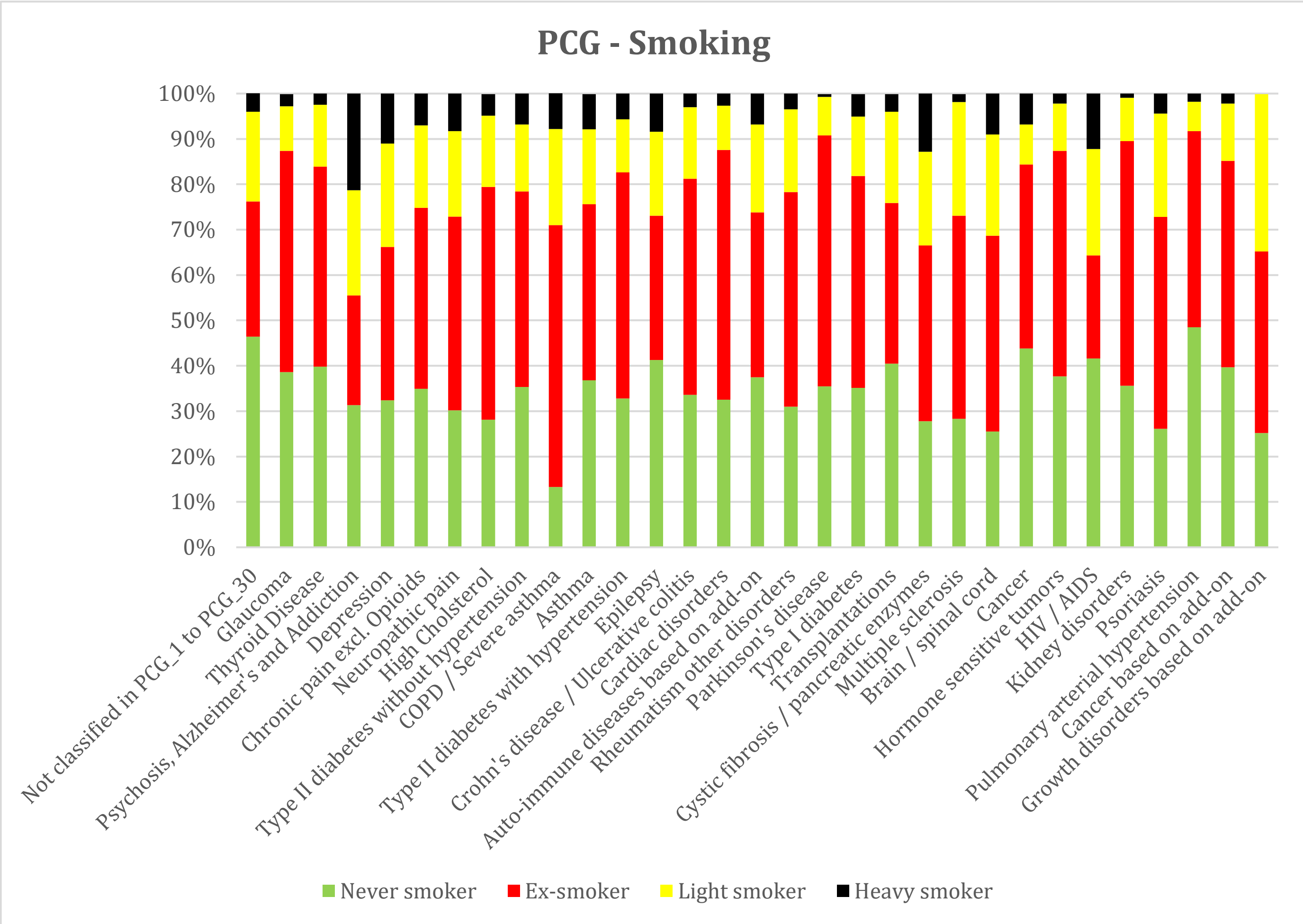

Figure 3. Frequencies of smoking subgroups within each PCG

Another observation that catches the eye is the high percentages of S_H in column 3, 20 and 25. Where psychosis, Alzheimer's and addiction do not have a significant cost-increasing effect, Cystic fibrosis / pancreatic enzymes surely have. The percentage of S_H here is three times the percentage of S_H in PCG_0. The high percentage of S_H in PCG_3 and PCG_25 can partly be explained by the lower average age in these groups. Another hypothesis is the high stress levels these groups (psychosis, Alzheimer, addiction, and HIV/AIDS) are exposed to. This might lead to considerable amounts of smoking. So, in that case smoking is not the cause but the effect of a diagnosis.

A third observation is the considerable difference in the percentage of S_E in many PCG's compared to PCG_0. COPD / severe asthma stands out especially. Almost 60% of the individuals who receive medication for severe asthma or COPD have at least a history with smoking. This is twice the frequency observed in the base group. Only 13% belong to the never smoking group. Furthermore, PCG_14, cardiac disorders, demonstrates a very high percentage of individuals with a smoking history. The correlations between PCG and S_L/S_H are probably less visible because people often stop smoking only when an (acute) medical indication occurs. This seems clearly visible in cardiac disorders' column.

To conclude, there are positive correlations between smoking behavior and almost all risk adjusters in the Dutch risk equalization model of 2016. S_H has a strong correlation with SOI and SES. Differences in healthcare expenditure may therefore not only have arisen due to differences in smoking behavior, but perhaps due to differences in access to health care, both financially and culturally. That is why it is important to include these variables in the sensitivity analysis. For the S_E-group, SOI and SES do not play a role in explaining higher health expenditure but MHCG, DMECG, DCG and HCCG do. All these cost-increasing risk adjusters are more common among S_E than S_N. Also, within the PCG's, the correlation is particularly visible for S_E. This will be biased in part by the age difference between the S_N and S_E. This bias will be eliminated when calculating the implicit compensations.

4.3: Implicit Compensation

For analyzing the presence of implicit compensation, the normative health expenses were first calculated according to the formula as presented in the Methods section. Four dummy risk adjusters were not included in the model: the morbidity-age interacted dummies (MAG). This was done because the additional predictive value was very limited, and it resulted in unusual results. Besides, the characteristics present in these dummies are also present in other risk adjuster dummies. The coefficients of all included risk adjusters are given in Appendix A. The model has a predictive value of 0.328, which is very close to the R-squared of the actual Dutch risk equalization model of 2016 (0.31) (McGuire & Van Kleef, 2018). In the calculation model, the coefficients for the risk adjusters are rounded off, due to practical reasons. This leads to minor discrepancies in the results.

In Table 3 the actual, normative and DemoNorm health expenses for each subgroup are demonstrated. For all four subgroups the actual, normative and DemoNorm expenses differ significantly tested by paired t-tests. What stands out most is the increasing values in the S_N-group when looking top to bottom, compared to the opposite trend seen in all three smoking groups. This downward trend is largest in the S_H-group and smallest in the S_E-group.

Subgroup	**Never-smoker (S_N)**	**Ex-smoker (S_E)**	**Light smoker (S_L)**	**Heavy smoker (S_H)**
Actual Health Expenses	€2,005.08 **	€3,101.75 **	€2,076.33 **	€2,634.03 **
Normative Health Expenses	€2,106.29 **	€3,074.63 **	€ 1,953.73 **	€2,319,.77 **
DemoNorm	€2,223.19 **	€2,994.05 **	€ 1,907.98 **	€1,937.67 **

Table 3. Actual, normative and DemoNorm health expenses per smoking subgroup (**; p-value <0.01)

The values presented in Table 3 can be used to calculate the following for each individual subgroup:

- profit from risk selection (PRS) (normative expenses minus actual expenses);
- implicit compensation (normative expenses minus DemoNorm expenses);
- over-expenses (actual expenses minus DemoNorm expenses);

based on smoking behavior. These are projected in Figure 4 for each subgroup.

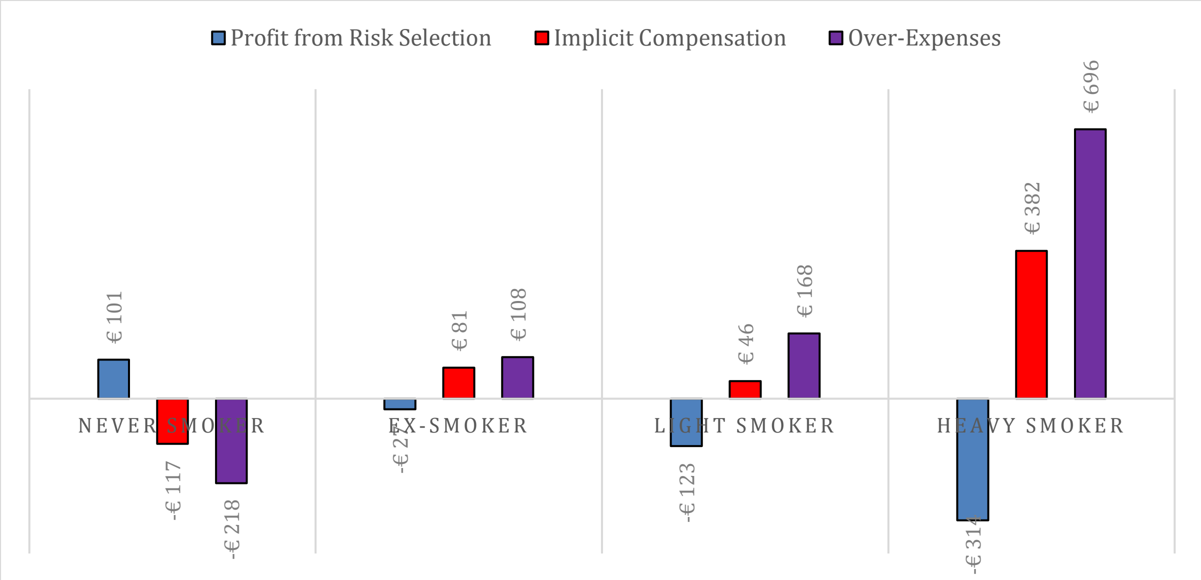

Figure 4. Mean PRS, implicit compensation and over-expenses per smoking subgroup

The PRS is only positive in the S_N-group, which means that there are incentives for risk selection based on smoking behavior for insurers. If insurers can identify (past) smoking behavior among consumers, they may try to attract those who have never smoked. The differences are significant and quite substantial. On average an insurer can make over €100 profit on never-smokers and more than €300 loss on heavy smokers.

The implicit compensation is positive in all the smoking groups, which means that for these groups higher normative expenses are granted than if only age and sex would be used for calculating the normative expenses. The S_N-group is rewarded with lower normative payments by the 2016 Dutch risk equalization model compared to the normative payment if only age and sex are regarded as legitimate risk adjusters. The differences are statistically significant. So, it can be concluded from this that implicit compensation is present based on smoking behavior. The largest implicit compensation is seen for the S_H-group: around €380 on average per person per year. The implicit compensation for S_L and S_E is much lower, respectively €45, and €80. The S_N-group shows a negative implicit compensation of around -€115. Altogether, a total implicit compensation of around €620 million per year in the Netherlands can be observed. However, the assumption must be made that only age and sex are a legitimate basis for compensation. This assumption will be relaxed in the sensitivity analysis further on.

Subtracting the DemoNorm expenses from the actual expenses leads to the over-expenses: the amount of actual health expenses that is higher than expected, based on only the age and sex of individuals. The S_H-group demonstrates the highest over-expenses of almost €700. In other words, their actual health expenses are almost €700 higher per year than what is expected purely on their age and sex. Positive over-expenses are seen in all smoking groups, while the over-expenses in the S_N-group are negative, i.e., their actual health expenses are lower than what can be expected based on their age and sex only. Altogether the total over-expenses for smoking is around €1.1 billion per year in the Netherlands.

To validate the results of the implicit compensation a sensitivity analysis was performed. Besides the DemoNorm, four additional models were used to calculate normative health expenses based on purely C-variables. The full sensitivity analysis can be found in Appendix C. Out of the four models, sensitivity-model 4 (SENS 4) had the highest predictive value and had most potential C-variables included. Next to age/sex, SENS 4 includes SOI, SES and REG as C-variables. This model will now be used to determine the extent of implicit compensation, instead of the DemoNorm. The results are shown in Figure 5.

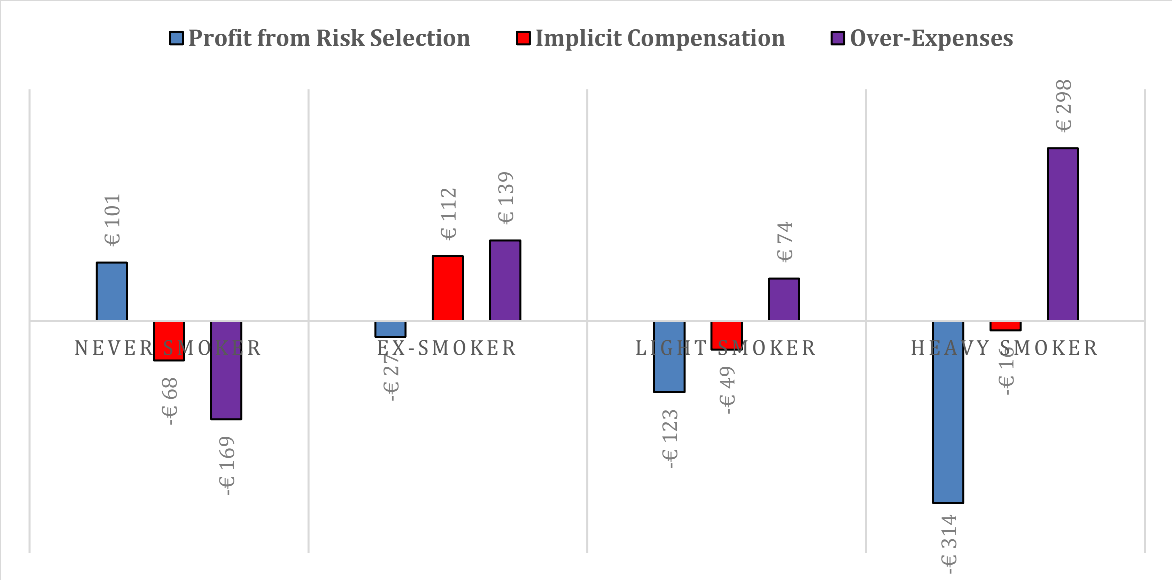

Figure 5. Mean PRS, implicit compensation and over-expenses per subgroup after sensitivity analysis

In Graph 3 the DemoNorm has been replaced by SENS 4 and this leads to quite different results as compared to Graph 2. The most striking difference can be seen in the S_H-group. The implicit compensation of more than €380 has been converted to a negative implicit compensation of around -€15. From this, it can be concluded that the initial implicit compensation of S_H did not arise from the inclusion of pharmaceutic or diagnostic information, but from the inclusion of SES, SOI and region. And, when looked at it in more detail, to these three variables, SOI does contribute most (see Appendix C). This result is in line with the earlier observed correlations between SOI, SES and smoking behavior.

Furthermore, the implicit compensation of S_L transforms from largely positive to slightly negative when additional C-variables are added. The S_E-group, however, shows an opposite trend. The implicit compensation is enlarged when more potential C-variables are added. The S_E-group is the only group with positive implicit compensation. This implicit compensation is partly countered by negative implicit compensation for the other two smoking groups, but not entirely as the S_N-group is still significantly below zero.

The total implicit compensation for smoking behavior in the Netherlands can be calculated by multiplying the extent of implicit compensation with the group sizes and then adding the three smoking groups together. This results in a total implicit compensation of smoking behavior of around €325 million per year. The total over-expenses of smoking behavior are, with SENS 4 instead of the DemoNorm, around €880 million per year in the Netherlands.

To conclude, when only age and sex are considered legitimate risk adjusters, implicit compensation is present in all three smoking subgroups and largest in the S_H-group. The S_N has a negative implicit compensation and is thus undercompensated. However, when SES, SOI and region are regarded as C-variables as well, the implicit compensation is only still positive in the S_E-group. The negative implicit compensation of the S_N-group is now closer to zero, so overall the extent of implicit compensation for smoking is smaller when more potential C-variables are added, although still very present.

4.4: Explicit Approach

The last part of the results demonstrates the impact the explicit approach has on calculating the normative health expenses compared to the conventional approach. The explicit method has been applied as described in the method section. Adding the three smoking dummy variables did not increase the R-squared (remained 0.328), but the predictive value did increase given the reduction of the mean square residual.

"Never-smokers" were added to the reference group and this resulted in a decrease from €811 to €709. The following coefficients were found for the three smoking dummies: ex-smoker (€136), light smoker (€236), heavy smoker (€443). So, even when controlled for all other risk adjusters, (past) smoking behavior is a predictor for higher healthcare expenses.

Figure 6 shows the results for subtracting the explicit normative healthcare expenses from the conventional normative healthcare expenses for everyone in the sample. As can be seen, the vast majority will not be rewarded considerable different. However, some individuals will be tagged with much lower normative payments when the explicit model is in place. The difference can in some very exceptional cases go up to even (more than) €1000 a year. These individuals can be found on the far-right end of the graph. There are also individuals who will be tagged with a higher normative payment when the explicit model is used. These individuals can be found on the far-left end of the graph.

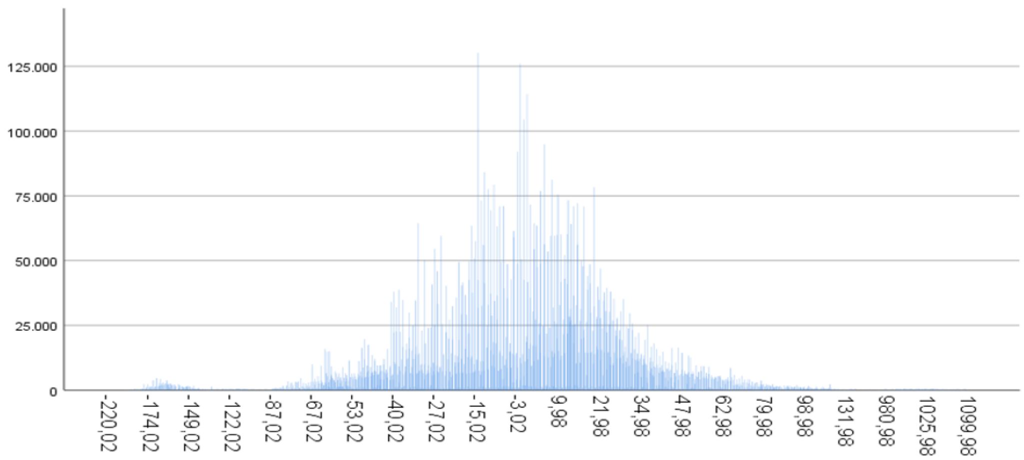

Figure 6. Differences conventional - explicit normative payments

To investigate whether the higher explicit normative expenses are more common among the smoking groups or among the never-smokers group, the mean difference per subgroup is presented in Figure 7.

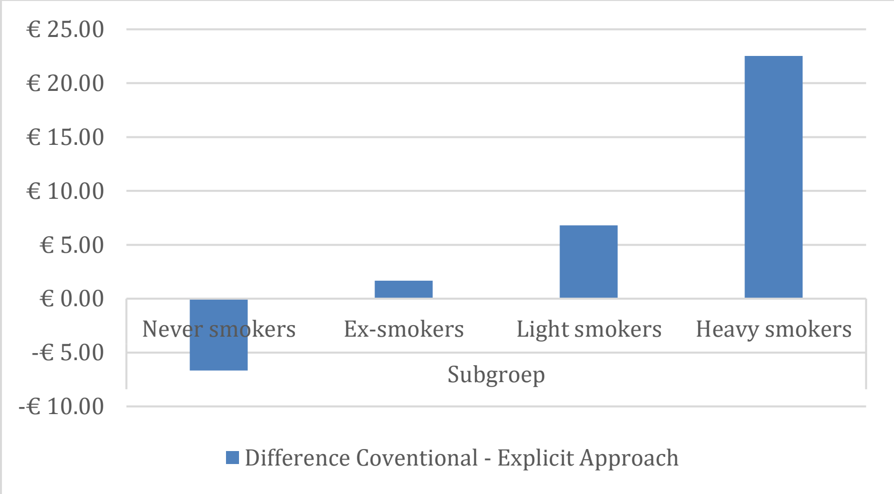

Figure 7. Mean difference of conventional - explicit normative expenses per subgroup

The differences between the two normative expenses were for all four subgroups statistically significant (paired t-tests). The three smoking groups have a positive mean difference indicating that the conventional approach led to higher normative payments compared to the explicit model. This mean difference is highest for the S_H-group (€22) and lowest for the S_E-group (€1). For the S_N-group the opposite holds true, and the explicit approach calculates higher normative payments. This difference is a little more than €6 per person per year on average. Across the system, the explicit approach redistributes approximately €30 million in the Netherlands per year from the smoking groups to the never-smokers group compared to the conventional approach.

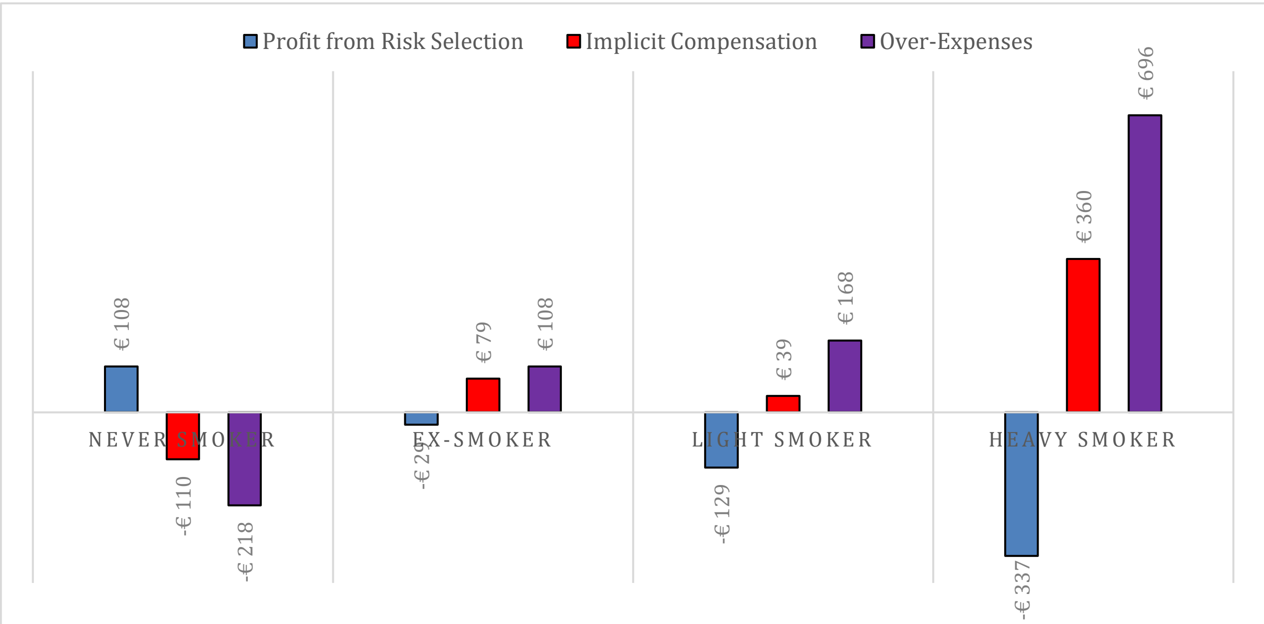

Figure 8. PRS, implicit compensation and over-expenses per subgroup with explicit approach

The change from conventional to explicit normative expenses will lead to a larger difference in PRS between the never-smokers and (ex-)smokers groups. So, the incentives for insurers to risk select based on an R-variable increase. This is because the normative expenses will increase for the never-smokers group, which already had a positive PRS. For the other groups the normative expenses decrease. With an already negative PRS, this will lead to an even more negative PRS. In addition, the explicit will theoretically eliminate all incentives for risk selection based on C-variables.

The change from conventional to explicit normative expenses will also lead to less implicit compensation. The normative expenses are higher for the S_N-group, with an unchanged DemoNorm, this results in a less negative implicit compensation. For the smoking groups the opposite holds true; the normative expenses are lower, resulting in less positive implicit compensation. However, it must be noted that the differences created by the explicit approach (€30 million) are not comparable with the total amount of implicit compensation of smoking behavior (€620 million to €590 million (DemoNorm) or €325 million to €295 million (SENS4)).

Chapter 5: Discussion

The final part of this study is the discussion. First, the key findings of this study are summarized. Second these key findings will be linked to the theoretical framework and introduction, and the implications will be explained. Then the study design will be evaluated. Finally, recommendations are made for further research and policy choices.

5.1: Key Findings

The first conclusion that can be drawn from this study is that there is a positive correlation between the risk adjusters of the 2016 Dutch risk equalization model and smoking behavior. This means that (past) smokers are more prevalent among individuals tagged with a cost-increasing risk adjuster. The effect is strong for heavy smokers compared to never-smokers in the SES and source of income dummies, and for the ex-smokers compared to never-smokers in the pharmaceutical cost group (especially for COPD/severe asthma), multiple-year high-cost group, and diagnostic cost group dummies. The correlation, as explained, between supposed C-variables and R-variables, combined with the use of the conventional approach, leads to omitted-variable bias. So, the effects of smoking behavior on healthcare spending are partly taken up by the risk adjusters, creating incentives for risk selection based on these risk adjusters. Here, however, the assumption must be made that insurers should be able to observe the smoking behavior of consumers for this problem to occur.

The presence of a positive correlation between smoking and all risk adjusters already hinted on the presence of implicit compensation based on smoking, however age and sex were still creating confounding bias.

Later this confounding bias is eliminated, by controlling for this in the DemoNorm model, and then it can be concluded that there is implicit compensation based on smoking behavior in the Dutch risk equalization model. For (ex-)smokers higher risk-adjusted subsidies are calculated than would result if only their age and sex would be considered. The group of never-smokers were given a risk-adjusted subsidy lower than what is expected based on their DemoNorm (-€117). The implicit compensation for smoking is biggest for heavy smokers (+€382) and substantially smaller, but still significantly positive, for ex-smokers (+€81) and light smokers (+€46).

However, results change when SES, source of income and region are also added to the DemoNorm. The implicit compensation for (past) smoking behavior stays present, albeit to a lesser extent. The most remarkable difference takes place within the heavy smokers group. The implicit compensation of around +€380 switches to a small negative implicit compensation (-€16). Moreover, for light smokers this implicit compensation becomes negative (-€49). For ex-smokers the extent of implicit compensation increases to over €100 per person per year on average. The negative implicit compensation of never-smokers stays negative, albeit to a lesser extent (-€68).

The last key finding of this study is that the explicit approach will redistribute the normative health expenses significantly different compared to the conventional approach, however the average differences per subgroup are small. The small difference is negative (explicit larger than conventional) for the never-smokers and positive for all smoking groups. The total implicit compensation of €620 million decrease to only €590 million. These changes in normative health expenses also theoretically lead to elimination of incentives for risk selection based on C-variables and increases the incentives for risk selection based on R-variables.

5.2: Implications of Key Findings

The implicit compensation found in this study can be classified as a sort of implicit cross-subsidy of hundreds of million euros per year from never-smokers to (past) smokers. As is already mentioned, it is at least questionable whether such type of cross-subsidies is desirable. The goal of the risk equalization system is to bring about equity, which has been defined as the absence of systematic disparities in health and in the major social determinants of health. Lifestyle, such as smoking, is normally not regarded as a social determinant of health (Braveman & Gruskin, 2003). Schokkaert and Van de Voorde (2006) also already stated that health differences, which originate from lifestyle differences, do not by definition require cost compensation. Therefore, it can be concluded that such a cross-subsidy for smoking behavior does not align with the rationale of risk equalization.

Besides, this cross-subsidy takes the responsibility of the financial risks exposed by smoking largely away from the individual. Smokers and non-smokers do after all pay the same price for care, although one generates higher healthcare costs than the other. Thus, there is not a financial incentive for individuals to stop (or to not start) smoking, or otherwise act preventively regarding health, in the current system. So, this implicit compensation of smoking behavior in the Dutch risk equalization system is generally unwanted.

An alternative approach is the explicit approach. This approach was first studied by Schokkaert and van de Voorde (2006). In their study they used a simple model, with one C- and one R-variable to investigate the incentives for risk selection based on these variables. The results of this thesis are well in line with the results of Schokkaert and van de Voorde, although the size of the results differ. Because they used only one C-variable dummy and one R-variable with a (very) large coefficient, the profit from risk selection (PRS) based on the C-variable is large. This thesis starts from the more realistic situation of multiple C-variables and R-variables with a lower coefficient. This leads to weaker incentives for risk selection based on C-variables than presented by Schokkaert and van de Voorde.

The explicit approach does have several advantages over the current approach of risk equalization. First, as this thesis shows, the explicit approach reduces the total implicit compensation for smoking behavior when added to the model as an R-variable. However, the overall decrease in implicit compensation is limited. A lower implicit compensation, due to higher normative payments for never-smokers and lower normative payments for (past) smokers, directly leads to a higher profit from risk selection based on smoking behavior, compared to the conventional approach. This forces health insurers to either risk select, or risk rate based on R-variables. Risk rating or risk selection based on smoking behavior can create an incentive for individuals to stop smoking. Adding financial incentives, on top of information/education interventions, significantly increases the effectiveness of smoking cessation programs (Volpp et al., 2009). Risk selection might, however, threaten the quality of care and risk rating might, threaten the affordability of care for specific individuals (Van de Ven, Van Kleef & Van Vliet, 2015).

If both risk rating is bounded and risk selection is made impossible by the government, or is incomplete due to a lack of information, there might be an incentive for health insurers to promote preventive healthcare themselves. One way to do so it to set up their own preventive health campaign. This seems to fit very well within the goals of the Dutch health care system. Preventive healthcare is very efficient, and when targeted accurately it will decrease differences in health (Brown, Platt, & Amos, 2014). Dutch health insurers already increasingly focus on preventive healthcare. In a recent call, the three biggest health insurers together ask for more attention by healthcare providers on preventive healthcare (van der Geest, 2021).

An example of such a preventive health care campaign is the Vitality program, of the South African health insurer Discovery, and in use by the Dutch insurer ASR. This program is based on a reward system that stimulates a healthy lifestyle. With a smartphone, and other wearable smart objects the insurer tracks the consumers' data and rewards if certain goals are met. The program seems to work well, as vitality members live longer on average than non-vitality members, according to a study of Discovery (Discovery Vitality, 2017). However, there are also serious doubts about such initiatives. The connected devices give the insurer precious data on people's lifestyle and health conditions. This data can be used to risk select in an even more effective way. Besides, these programs overall attract healthier and younger consumers to start with, precisely because this category is more attracted by the technological devices offered by the insurer (Silvello & Procaccini, 2019). These programs thus seem noble but might just be another way for insurers to risk select.

Another advantage that the explicit approach has over the conventional approach, that it theoretically eliminates all incentives for risk selection and risk rating based on C-variables (Schokkaert & Van de Voorde, 2006). This advantage becomes even more important when government would allow (limited) risk rating, to create financial incentives for individuals to improve their lifestyle. Risk rating based on C-variables, which is still present in the conventional approach, is not in line with the values that are central to the Dutch health care system because it is a threat to equal access to and the quality of care.

However, as already mentioned in the theoretical framework, and what should not be underestimated, is the assumption that comes with the explicit approach. Insurers should be capable to observe the lifestyle variable, or other R-variable, to make the explicit approach work fair. Because if this is not the case, the explicit model will generate incentives for risk selection/risk rating based on C-variables and the conventional model will not. So, when using the explicit model only information that is available by the insurer should be included (Schokkaert & Van de Voorde, 2006).

5.3: Evaluation of Study Design

To evaluate, the data collection, storage, and linkage were performed by independent and reliable public administrative bodies who have a long history of processing large amounts of data. The data can therefore be described as trustworthy. Besides the strong reliability of the data, the quantity of the data is also an advantage. Data about all risk adjuster dummies, demographics, healthcare costs and lifestyle are available and linked at an individual level. This strength is increased by making the data representative for the entire Dutch population (above 19 years old). A possible disadvantage is the use of somewhat older data; the smoking information dates from nine years before the analysis of the information. Although the number of smokers decreased over the last years, smoking is still very prominently present in Dutch society (Centraal Bureau voor de Statistiek, 2019). Besides, the system of risk equalization essentially remained the same between 2016 and 2021.

The advantages of the subdivision of the four (non or past) smoking groups, have already been discussed. However, the subdivision does also have some downfalls. It does for instance not allow the measurement of the effect of passive smoking. Unfortunately, there is no data available for this, however it can have serious health effects (Cao, Yang, Gan, & Lu, 2015). Albeit that passive smoking is probably more likely to be treated as a C-variable than an R-variable compared to active smoking because the individual is more often less responsible for the exposed risk. In addition, pack-years are not included in the subdivision. Pack-years is used to describe the number of cigarettes someone smoked over their lifetime, i.e., two packs of cigarettes a day for fifty years equals to a hundred pack years. This could have been useful to make a more valid distinction between the light and heavy smokers. It could have been helpful to make a better distinction within the ex-smokers group. This group now also included respondents who might have smoked only a handful of cigarettes in their live. It might lead to under- or overestimation of the results. This problem could also have been prevented by stating the relevant survey question differently, such as: *‘Have you smoked regularly in the past?’* or ask respondents for their number of pack-years.

Besides passive smoking, another variable is also missing, stress. Stress might play an important role in the correlation between smoking and health expenses. It could be hypothesized that being (chronically) ill and thus have higher healthcare expenses leads to more stress, which one step further leads to more smoking. In that case, smoking is not the cause of the higher health expenses, but the consequence.

Another part of the method that requires further evaluation is the model used to calculate the implicit compensation of the R-variable 'smoking behavior'. An essential part of this model is the firm distinction between C- and R-variables. As has already been discussed, that distinction is in a gray area. This study does not aim to classify which risk adjusters do and which do not require compensation. To stay away from this gray area, initially, it was decided to take only age and sex as C-variables, and smoking behavior as R-variable. However, to strengthen the internal validity a sensitivity analysis has been performed with more possible C-variables included. It must be stated that introducing too many variables may lead to underestimation of the implicit compensation and not enough variables to an overestimation. The introduction of social-economic status, region, and source of income as C-variables may not be viewed as remarkable, but there are arguments to be made to not classify them as such. Socio-economic variables do indirectly influence health and the effect is mediated by, at least partly, unknown mediators. One of these mediators could very well be a difference in behavior towards healthcare between individuals of different social classes. This difference in behavior could originate from a difference in educational or economic background (possible reason to classify it as a C-variable). However, this difference could also be explained by a difference in attitude or culture towards (preventive) healthcare (possible reason to classify it as an R-variable).

Later in the analysis, when applying the explicit approach to the Dutch risk equalization system, only one risk adjuster is classified as R-variable: smoking behavior. Here too, an attempt has been made to stay away from the gray area, and therefore it has been decided to designate only one, more obvious, R-variable. Although lifestyle variables are clearly the patients’ own responsibility, there are also arguments to be made to regard them as C-variables. For instance, lifestyle is often influenced by circumstances that are not within the influence of the individual, such as parental education. The more controversial potential R-variables, multiple-year high-cost groups for example, are not classified as such in this thesis.

Furthermore, other lifestyle variables, such as alcohol consumption, are potential R-variables. These variables have not been included for simplification. The more variables are classified as R-variables in the explicit model, the more the normative healthcare costs will deviate from the actual healthcare costs. This will lead to stronger incentives for risk selection or preventive healthcare programs by insurers, and less implicit compensation for lifestyle. It will, however, be at the expense of implicit cross-subsidies from people in good health to those in poorer health.

A weakness of this study is the absence of a full model of insurer behavior. The effects of the explicit approach regarding insurer behavior are based upon the simple assumption that health insurers seek to make as much as profit as possible. The exact effects of the explicit model should be investigated with more attention to behavioral analyses of health insurers.

Finally, a reflection on the generalizability of the study. The study addresses a problem that is not limited to the Netherlands. The affordability of healthcare in the future and the call for more prevention in healthcare are topics that are increasingly higher on the agenda in many (especially Western) countries. In addition, smoking is also common in all these countries. The conventional approach, as it works in the Netherlands, is also very common in other countries. Until now, only Belgium uses the explicit model (McGuire & Van Kleef, 2018). This all increases the generalizability of the results of this study. Implications derived from the key findings are on the other hand only to a certain extent generalizable. The health insurance system, including the risk equalization model, in the Netherlands is quite unique. The freedom of insurers and payment flows differ per country. That makes it difficult to make similar policy recommendations for other countries.

To conclude, the study results have a high degree of validity and generalizability, however it can be improved. The amount of data used was extensive, however more information on passive smoking and stress could enhance the validity of the results. Finally, the results are also applicable outside the given context.

5.4: Conclusion and Recommendations

To conclude, there is a strong positive correlation between smoking behavior and almost all (cost-increasing) risk adjusters of the Dutch risk equalization model. This indicates the presence of incentives for risk selection based on C-variables. Besides, there is serious implicit compensation based on smoking behavior in the Dutch risk equalization model. To some extent, this implicit compensation can be explained through SES and source of income differences between never-smokers and (past) smokers. The explicit approach calculates the normative healthcare expenses significantly different compared to the conventional approach. Higher normative expenses for never-smokers and an opposite change for the (past) smokers is seen, leading to less implicit compensation and stronger incentives to risk select/rate based on smoking behavior. So, the explicit approach is potentially favorable over the conventional approach as it eliminates incentives to risk select based on C- variables, decreases the implicit compensation for lifestyle variables, and increases incentives (for the individual or insurer) for preventive healthcare. It ties in well with the goals of accessibility, efficiency, and quality of care.

A transition towards the explicit model would fit in well with the goals of risk equalization in the Netherlands and should also be considered seriously. There are however assumptions and practical issues that need to be clarified before implementation. It is crucial to investigate to what extent healthcare insurers have insight into the lifestyle of consumers. For the explicit approach to function, health insurers must be able to observe the differences in lifestyle among consumers. All health insurers must be able to obtain and use the same information to maintain a level playing field. Besides, this study only focuses on one lifestyle variable, including more R-variables is necessary to get an even better understanding of the current situation. In further research there must also be more attention to behavioral analyses of insurers. Besides, it is important to further study how risk selection, even based on R-variables can be prevented as much as possible because risk selection might lead to lower quality of care. Another, more ethical, question concerns the desirability that healthcare insurers have so much (personal) data of consumers, even if it is not allowed to use this for risk selection. Finally, this thesis indirectly raises the question of how to deal with risk selection based on a lifestyle variable.

Appendices

Appendix A: Overview of Risk Adjusters of Dutch Risk Equalization Model 2016

Name	**Description**	**Coefficient (conventional)**	**Coefficient (explicit)**
ASG_6	Male, 18-24	Reference	Reference
ASG_7	Male, 25-29	30.939 *	21.873 *
ASG_8	Male, 30-34	-138.616 **	-161.778 **
ASG_9	Male, 35-39	-157.32 **	-154.557 **
ASG_10	Male, 40-44	28.214 *	33.822 **
ASG_11	Male, 45-49	52.416 **	56.26 **
ASG_12	Male, 50-54	381.062 **	373.017 **
ASG_13	Male, 55-59	623.981 **	605.662 **
ASG_14	Male, 60-64	852.505 **	839.737 **
ASG_15	Male, 65-69	1733.777 **	1704.639 **
ASG_16	Male, 70-74	1809.398 **	1789.585 **
ASG_17	Male, 75-79	2137.384 **	2121.106 **
ASG_18	Male, 80-84	2313.08 **	2298.566 **
ASG_19	Male, 85-89	3673.757 **	3661.812 **
ASG_20	Male, 90+	3358.124 **	3352.816 **
ASG_26	Female, 18-24	317.79 **	336.321 **
ASG_27	Female, 25-29	698.156 **	705.469 **
ASG_28	Female, 30-34	889.922 **	895.569 **
ASG_29	Female, 35-39	473.528 **	505.259 **
ASG_30	Female, 40-44	178.942 **	209.119 **
ASG_31	Female, 45-49	179,.52 **	200.954 **
ASG_32	Female, 50-54	233.272 **	237.305 **
ASG_33	Female, 55-59	465.691 **	464.178 **
ASG_34	Female, 60-64	534.321 **	543.52 **
ASG_35	Female, 65-69	1006.365 **	1012.586 **
ASG_36	Female, 70-74	1222.625 **	1242.726 **
ASG_37	Female, 75-79	1502.214 **	1535.84 **

Name	**Description**	**Coefficient (conventional)**	**Coefficient (explicit)**
MHCG_0	Not classified in MHCG_1 to MHCG_6	Reference	Reference
MHCG_1	In 2 previous years costs in 3 previous years in top 10%	1928.876 **	1926.117 **
MHCG_2	Costs in 3 previous years in top 15%	2301.411 **	2302.089 **
MHCG_3	Costs in 3 previous years in top 10%	3773.181 **	3771.954 **
MHCG_4	Costs in 3 previous years in top 7%	5858.249 **	5862.677 **
MHCG_5	Costs in 3 previous years in top 4%	9983.173 **	9986.997 **
MHCG_6	Costs in 3 previous years costs 1.5%	25755.02 **	25771.069 **
DMECG_0	Not classified in DMECG_1 to DMECG_4	Reference	Reference
DMECG_1	Insulin infusion pumps	-185.163 **	-179.495 **
DMECG_2	Catheters / urine collection bags	2313.665 **	2321.73 **
DMECG_3	Steaming aids	1477.197 **	1470.763 **
DMECG_4	Trachea stoma aids	1323.069 **	1333.791 **
MAG_1	No morbidity, under 65 years old	Not included in the model	Not included in the model
MAG_2	No morbidity, 65+ years old	Not included in the model	Not included in the model
MAG_3	Morbidity, under 65 years old	Not included in the model	Not included in the model
MAG_4	Morbidity, 65+ years old	Not included in the model	Not included in the model
SOI_0	65+ years old	Reference	Reference
SOI_1	18-34 years, completely disabled	15618.252 **	15640.673 **
SOI_2	35-44 years, completely disabled	-18.992	-43.781
SOI_3	45-54 years, completely disabled	2276.512 **	2255.898 **
SOI_4	55-64 years, completely disabled	1140.892 **	1125.145 **
SOI_5	18-34 years, (other) disabled	481.119 **	489.674 **
SOI_6	35-44 years, (other) disabled	796.367 **	755.881 **
SOI_7	45-54 years, (other) disabled	807.032 **	776.643 **
SOI_8	55-64 years, (other) disabled	613.257 **	597.401 **
SOI_9	18-34 years, social security beneficiaries	61.197 **	58.267 **
SOI_10	35-44 years, social security beneficiaries	300.565 **	279.635 **

ASG_38	Female, 80-84	1870.815 **	1916.166 **
ASG_39	Female, 85-89	2782.757 **	2838.724 **
ASG_40	Female, 90+	4387.711 **	4458.088 **
PCG_0	Not classified in PCG_1 to PCG_30	-404.523 **	-403.199 **
PCG_1	Glaucoma	598.549 **	604.148 **
PCG_2	Thyroid Disease	151.124 **	156.228 **
PCG_3	Psychosis, Alzheimer's, and Addiction	-4.538	-50.798 *
PCG_4	Depression	71.007 **	39.686 **
PCG_5	Chronic pain excl. Opioids	778.963 **	771.533 **
PCG_6	Neuropathic pain	2388.247 **	2377.455 **
PCG_7	High Cholesterol	157.683 **	146.482 **
PCG_8	Type II diabetes without hypertension	530.627 **	530.068 **
PCG_9	COPD / Severe asthma	1937.99 **	1892.869 **
PCG_10	Asthma	519.966 **	507.497 **
PCG_11	Type II diabetes with hypertension	880.092 **	875.382 **
PCG_12	Epilepsy	541.635 **	547.606 **
PCG_13	Crohn's disease / Ulcerative colitis	1270.837 **	1269.703 **
PCG_14	Cardiac disorders	2235.379 **	2234.051 **
PCG_15	Auto-immune diseases based on add-on	13508.245 **	13502.014 **
PCG_16	Rheumatism other disorders	1275.715 **	1272.176 **
PCG_17	Parkinson's disease	1243.174 **	1256.265 **
PCG_18	Type I diabetes	1668.669 **	1669.265 **
PCG_19	Transplantations	-374.054 **	-366.898 **
PCG_20	Cystic fibrosis / pancreatic enzymes	3920.951 **	3889.512 **
PCG_21	Multiple sclerosis	64.733	55.534
PCG_22	Brain / spinal cord	4118.925 **	4100.629 **
PCG_23	Cancer	-621.567 **	-621.367 **
PCG_24	Hormone sensitive tumors	431.614 **	436.731 **
PCG_25	HIV / AIDS	3205.994 **	3187.365 **
PCG_26	Kidney disorders	8708.019 **	8720.735 **
PCG_27	Psoriasis	369.167 **	350.411 **
PCG_28	Pulmonary arterial hypertension	10468.584 **	10486.499 **

SOI_11	45-54 years, social security beneficiaries	811.537	783.735 **
SOI_12	55-64 years, social security beneficiaries	170.376 **	157,032 **
SOI_13	18-34 years, student	-347.752 **	-308.966 **
SOI_17	18-34 years, self-employed	-249.194 **	-228.223 **
SOI_18	35-44 years, self-employed	32.734 *	30.911 *
SOI_19	45-54 years, self-employed	-168,765**	-163.538 **
SOI_20	55-64 years, self-employed	16.5	24.425
SOI_21	18-34 years, highly educated	-131.244 **	-83.859 **
SOI_25	18-34 years, other	Reference	Reference
SOI_26	35-44 years, other	Reference	Reference
SOI_27	45-54 years, other	Reference	Reference
SOI_28	55-64 years, other	Reference	Reference
SES_1	!8-64 years, 15+ residents at address (stayer)	106.913 **	60.941
SES_2	65+ years, 15+ residents at address (stayer)	-3750.743 **	-3774.378 **
SES_4	!8-64 years, 15+ residents at address (new)	1654.514 **	1577.487 **
SES_5	65+ years, 15+ residents at address (new)	3305.831 **	3298.235 **
SES_7	18-64 years, lowest 20% of income group	58.817 **	28.73 **
SES_8	65+ years, lowest 20% of income group	553.375 **	546.745 **
SES_10	18-64 years, 20% - 39% of income group	61.16 **	38.741 **
SES_11	65+ years, lowest 20% - 39% of income group	-21.945	-26.202 *
SES_13	18-64 years, lowest 40% - 69% of income group	77.668 **	64.783 **
SES_14	65+ years, lowest 40% - 69% of income group	Reference	Reference
SES_16	18-64 years, highest 30% of income group	Reference	Reference
SES_17	65+ years, highest 30% of income group	-211.071 **	-206.1 **
REG_1	Zip-code area 1	140.909 **	139.296 **
REG_2	Zip-code area 2	107.892 **	102.144 **
REG_3	Zip-code area 3	191.686 **	188.673 **
REG_4	Zip-code area 4	180.507 **	180.056 **
REG_5	Zip-code area 5	163.705 **	163.681**
REG_6	Zip-code area 6	208.511 **	203.889 **
REG_7	Zip-code area 7	187.926 **	190.352 **
REG_8	Zip-code area 8	176.238 **	177.475 **

PCG_29	Cancer based on add-on	11931.096 **	11936.667 **	REG_9	Zip-code area 9	138.005 **	139.894 **
PCG_30	Growth disorders based on add-on	1692.984 **	1668.658 **	REG_10	Zip-code area 10	Reference	Reference
DCG_0	Not classified in DCG_1 to DCG_15	Reference	Reference	HCCG_0	Not classified in HCCG_1 to HCCG_4	Reference	Reference
DCG_1	Group of diagnoses [1]	860.349 **	868.756 **	HCCG_1	Top 2.5% of home care costs	2325.225 **	2324.668 **
DCG_2	Group of diagnoses	758.052 **	757.133 **	HCCG_2	Top 1.5% of home care costs	7054.334 **	7058.32**
DCG_3	Group of diagnoses	1376.183 **	1373.212 **	HCCG_3	Top 0.5% of home care costs	12064.678 **	12076.54 **
DCG_4	Group of diagnoses	2709.041 **	2703.22 **	HCCG_4	Top 0.25% of home care costs	23664.468 **	23664.505 **
DCG_5	Group of diagnoses	2851.299 **	2843.799 **	GCG_0	Not classified in GCG_1	Reference	Reference
DCG_6	Group of diagnoses	2961.202 **	2942.669 **	GCG_1	Top 0.275% of geriatric revalidation care costs	870.225 **	874.064 **
DCG_7	Group of diagnoses	5291.512 **	5287.273 **	PTCG_0	Not classified in PTCG_1	Reference	Reference
DCG_8	Group of diagnoses	3424.276 **	3422.099 **	PTCG_1	Top 2.0% of physio therapeutic care costs	742.019 **	750.982 **
DCG_9	Group of diagnoses	10527.799 **	10542.613 **	Never-smoker	Never smoked	Reference	Reference
DCG_10	Group of diagnoses	5972.697 **	5975.749 **	Ex_smoker	Ex-smoker	Not included in the model	136.123 **
DCG_11	Group of diagnoses	16995.765 **	17000.137 **	Light_smoker	Smokers (<20 cigarettes)	Not included in the model	236.899 **
DCG_12	Group of diagnoses	18325.199 **	18319.885 **	Heavy_smoker	Smokers (>=20 cigarettes)	Not included in the model	443.026 **
DCG_13	Group of diagnoses	17834.208 **	17860.131 **				
DCG_14	Hemophilia	11122.839 **	11080.306 **	Reference		811.292	709.09
DCG_15	(Home) dialysis	65917.647 **	65928.885 **		(*; p-value <0.05 / **; p-value <0.01)		

Appendix B: Frequency Tables Risk Adjusters per Subgroup

Age	SN	SE	SL	SH
Under 65 years	84.0%	71.2%	89.9%	91.7%
65 + years	16.0%	28.8%	10.1%	8.3%

Sex	SN	SE	SL	SH
Female	56.93%	47.75%	44.63%	39.22%
Male	43.07%	52.25%	55.37%	60.78%

REG	SN	SE	SL	SH
1	9.8%	8.6%	11.1%	12.6%
2	9.8%	9.8%	10.8%	13.5%
3	9.9%	10.1%	10.4%	11.0%
4	9.9%	10.0%	9.7%	9.5%

DCG	SN	SE	SL	SH
0	91.0%	84.3%	90.9%	89.1%
1	1.6%	2.4%	1.3%	1.3%
2	2.1%	3.3%	2.2%	2.4%
3	2.2%	4.0%	2.3%	2.7%

[1] List of diagnoses in DCG_1 to DCG_15 derived from National Health Care Institute (2015a)

5	10.0%	10.3%	10.1%	8.7%
6	9.6%	10.5%	9.8%	10.6%
7	10.3%	10.2%	9.4%	8.3%
8	10.1%	10.2%	9.6%	8.6%
9	10.1%	10.5%	9.5%	8.2%
10	10.3%	9.9%	9.7%	9.0%
Total (1-9)	**89.5%**	**90.2%**	**90.4%**	**91.0%**

SOI	SN	SE	SL	SH
0	17.8%	33.0%	12.2%	11.0%
1	0.0%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.1%	0.1%
3	0.1%	0.1%	0.1%	0.2%
4	0.1%	0.3%	0.2%	0.4%
5	1.5%	0.5%	1.6%	3.0%
6	0.6%	0.6%	0.9%	2.6%
7	1.0%	1.1%	1.6%	4.0%
8	1.1%	2.8%	2.3%	4.4%
9	0.9%	0.3%	1.6%	1.5%
10	0.8%	0.4%	1.1%	2.0%
11	0.9%	0.6%	1.6%	3.2%
12	0.6%	0.7%	1.1%	2.2%
13	5.5%	1.0%	4.7%	1.0%
17	1.3%	0.6%	1.6%	1.2%
18	1.8%	1.2%	1.9%	1.8%
19	1.8%	1.7%	1.5%	2.4%
20	0.8%	1.5%	0.9%	1.2%
21	7.4%	2.3%	4.6%	1.3%
25	13.0%	6.4%	19.3%	13.6%
26	17.4%	11.1%	14.8%	13.0%
27	16.2%	15.4%	15.0%	17.2%

4	1.0%	2.0%	1.2%	1.5%
5	0.6%	1.0%	0.6%	0.8%
6	0.6%	1.5%	0.8%	1.1%
7	0.2%	0.4%	0.3%	0.4%
8	0.1%	0.1%	0.1%	0.1%
9	0.3%	0.5%	0.2%	0.2%
10	0.1%	0.1%	0.0%	0.1%
11	0.1%	0.2%	0.1%	0.1%
12	0.0%	0.1%	0.0%	0.0%
13	0.0%	0.0%	0.0%	0.0%
14	0.0%	0.0%	0.0%	0.0%
15	0.0%	0.1%	0.0%	0.0%
Total 1-15	**8.9%**	**15.7%**	**9.1%**	**10.7%**

PTCG	SN	SE	SL	SH
0	97.8%	96.7%	98.2%	98.2%
1	2.2%	3.3%	1.8%	1.8%

GCG	SN	SE	SL	SH
0	99.8%	99.7%	99.9%	99.8%
1	0.2%	0.3%	0.1%	0.2%

HCCG	SN	SE	SL	SH
0	97.5%	33.1%	19.1%	4.5%
1	0.9%	1.3%	0.6%	0.8%
2	1.0%	1.2%	0.6%	0.6%
3	0.3%	0.3%	0.1%	0.2%
4	0.2%	0.3%	0.1%	0.2%
Total 1-4	**2.4%**	**3.1%**	**1.4%**	**1.8%**

MHCG	SN	SE	SL	SH

28	9.3%	18.4%	11.1%	12.8%
Total (1, 3-12 & 18)	**9.4%**	**8.6%**	**14.0%**	**25.3%**

SES	SN	SE	SL	SH
1	0.4%	0.0%	0.6%	1.4%
2	0.4%	0.5%	0.1%	0.6%
4	0.1%	0.0%	0.1%	0.3%
5	0.2%	0.2%	0.1%	0.1%
7	14.7%	10.4%	21.2%	27.6%
8	4.2%	5.2%	2.8%	2.8%
10	15.2%	13.1%	19.6%	20.9%
11	3.3%	6.4%	2.4%	2.0%
13	24.5%	21.6%	25.4%	23.1%
14	4.8%	10.5%	3.5%	2.8%
16	27.3%	21.9%	21.0%	15.7%
17	5.0%	10.2%	3.3%	2.7%
Total (1, 4-10 & 13)	**59.3%**	**50.5%**	**69.8%**	**76.2%**

PCG	SN	SE	SL	SH
0	81.7%	68.3%	79.8%	68.9%
1	1.0%	1.6%	0.6%	0.7%
2	2.0%	2.9%	1.6%	1.2%
3	0.5%	0.5%	0.9%	3.3%
4	2.6%	3.5%	4.2%	8.4%
5	1.2%	1.8%	1.5%	2.3%
6	0.2%	0.3%	0.2%	0.4%
7	4.6%	11.0%	5.9%	7.7%
8	0.7%	1.1%	0.6%	1.2%
9	0.5%	2.6%	1.7%	2.6%
10	2.1%	2.9%	2.2%	4.4%
11	1.4%	2.7%	1.1%	2.3%

0	94.7%	90.2%	94.8%	92.5%
1	1.0%	1.6%	1.0%	1.3%
2	2.2%	4.0%	1.9%	3.0%
3	0.9%	1.9%	1.0%	1.4%
4	0.7%	1.4%	0.7%	0.9%
5	0.4%	0.7%	0.5%	0.6%
6	0.1%	0.2%	0.1%	0.2%
Total 1-6	**5.3%**	**9.8%**	**5.2%**	**7.4%**

DMECG	SN	SE	SL	SH
0	99.2%	98.4%	99.3%	99.2%
1	0.1%	0.1%	0.1%	0.1%
2	0.4%	0.8%	0.3%	0.3%
3	0.3%	0.6%	0.3%	0.3%
4	0.0%	0.0%	0.0%	0.0%
Total 2-4	**0.7%**	**1.4%**	**0.6%**	**0.6%**

PCG	SN	SE	SL	SH
0	46.4%	29.8%	19.8%	4.1%
1	38.6%	48.8%	9.8%	2.7%
2	39.8%	44.1%	13.6%	2.5%
3	31.3%	24.2%	23.2%	21.3%
4	32.4%	33.8%	22.8%	11.0%
5	34.9%	39.9%	18.2%	7.0%
6	30.2%	42.7%	18.8%	8.3%
7	28.1%	51.3%	15.7%	4.8%
8	35.3%	43.1%	14.8%	6.8%
9	13.3%	57.7%	21.2%	7.9%
10	36.8%	38.8%	16.5%	7.8%
11	32.8%	49.8%	11.7%	5.7%

12	0.6%	0.6%	0.6%	1.1%
13	0.2%	0.4%	0.2%	0.2%
14	2.0%	4.4%	1.4%	1.6%
15	0.2%	0.3%	0.3%	0.4%
16	0.3%	0.5%	0.4%	0.3%
17	0.1%	0.3%	0.1%	0.0%
18	1.3%	2.2%	1.1%	1.8%
19	0.2%	0.2%	0.2%	0.2%
20	0.0%	0.0%	0.0%	0.1%
21	0.0%	0.1%	0.1%	0.0%
22	0.0%	0.1%	0.0%	0.1%
23	0.0%	0.0%	0.0%	0.0%
24	0.4%	0.6%	0.2%	0.2%
25	0.1%	0.1%	0.1%	0.3%
26	0.1%	0.1%	0.0%	0.0%
27	0.1%	0.2%	0.2%	0.2%
28	0,0%	0,0%	0.0%	0.0%
29	0.2%	0.2%	0.1%	0.1%
30	0.0%	0.0%	0.0%	0.0%
Total excl. 0, 3, 19 & 23	**21.9%**	**40.5%**	**24.4%**	**37.6%**

12	41.3%	31.8%	18.5%	8.4%
13	33.6%	47.6%	15.8%	3.0%
14	32.5%	55.1%	9.7%	2.7%
15	37.5%	36.3%	19.4%	6.8%
16	31.0%	47.3%	18.2%	3.5%
17	35.5%	55.3%	8.5%	0.6%
18	35.1%	46.7%	13.1%	5.0%
19	40.5%	35.4%	20.1%	3.9%
20	27.8%	38.7%	20.7%	12.80%
21	28.3%	44.8%	25.0%	1.8%
22	25.5%	43.2%	22.3%	9.0%
23	43.8%	40.6%	8.8%	6.8%
24	37.7%	49.7%	10.4%	2.2%
25	41.6%	22.7%	23.5%	12.2%
26	35.6%	53.9%	9.6%	0.9%
27	26.1%	46.7%	22.8%	4.4%
28	48.5%	43.2%	6.5%	1.8%
29	39.7%	45.5%	12.6%	2.2%
30	25.2%	40.0%	34.7%	0.0%

Appendix C: Tables Sensitivity Analysis

Sensitivity analysis	**R-squared**	**Never-smoker**	**Ex-smoker**	**Light smoker**	**Heavy smoker**
Actual Health Expenses		€2,005.08	€3,101.75	€2,076.33	€2,634.03
Normative Health Expenses	0.328	€2,106.29	€3,074.63	€1,953.73	€2,319.77
DemoNorm		€2,223.19	€2,994.05	€1,907.98	€1,937.67
Age-sex-region (SENS 1)	0.060	€2,223.33	€2,991.25	€1,918.10	€1,961.29

Age-sex-soi (SENS 2)	0.073	€2,179.60	€2,979.30	€1,970.06	€2,285.49
Age-sex-ses (SENS 3)	0.065	€2,207.48	€2,970.56	€1,969.91	€2,071.99
Age-sex-ses-soi-region (SENS 4)	0.078	€2,174.58	€2,962.73	€2,002.77	€2,336.04
Difference DemoNorm - SENS 4		€48.62	€31.32	-€94.79	-€398.37

Subgroups	**Never-smoker**	**Ex-smoker**	**Light smoker**	**Heavy smoker**
Actual Health Expenses	€2,005.08 **	€3,101.75 **	€2,076.33 **	€2,634.03 **
Normative Health Expenses	€2,106.29 **	€3,074.63 **	€1,953.73 **	€2,319.77 **
SENS 4	€2,174.58 **	€2,962.73 **	€2,002.77 **	€2,336.04 **

Significance tested using paired t-tests (12x).

Appendix D: Tables Explicit Approach

Approach type	**Never-smoker**	**Ex-smoker**	**Light smoker**	**Heavy smoker**
Conventional normative expenses	€2,106.29	€3,074.63	€1,953.73	€2,319.77
Explicit normative expenses	€2,112.96	€3,072.96	€1,946.92	€2,297.25

Subgroup	**Never smoker**	**Ex-smoker**	**Light smoker**	**Heavy smoker**
Actual Health Expenses	€2,005.08	€3,101.75	€2,076.33	€2,634.03
Normative Health Expenses (explicit)	€2,112.96	€3,072.96	€1,946.92	€2,297.25
DemoNorm	€2,223.19	€2,994.05	€1,907.98	€1,937.67
Profit from Risk Selection	€107.88	-€28.79	-€129.41	-€336.78
Implicit Compensation	-€110.23	€78.91	€38.94	€359.58
Over-Expenses	-€218.11	€107.70	€168.35	€696.37

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