The added value of the risk adjusters ‘socioeconomic status’ and ‘source of income’ in the Dutch risk equalization model for mental care

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Abstract

This thesis analyzes the added value of the risk adjusters ‘socioeconomic status’ and ‘source of income’ in the Dutch risk equalization model for mental care. To avoid risk selection in the Netherlands, there is a risk equalization (RE) system. The RE system in the Netherlands works through payment weights determined by risk adjusters and is based on three models for three different types of care: somatic health care, mental health care and out-of-pocket payments. All 3 of these models are growing in complexity, where the risk adjusters SES and SOI are a substantial part of. After a qualitative analysis of how these risk adjusters perform and their influence on selection incentives for different subgroups in the mental health RE system without any other risk adjuster it was found that the mean difference in financial results ranged from -131 to 1307. The analysis was also conducted on the current RE system where a mean difference in financial results ranging from -84 to 312 euros was found. When comparing the potential and the actual added benefit from SES and SOI, it was found that the explanatory power of the risk adjusters on average has been taken over by other risk adjusters for about 90%. Some subgroups that were analyzed are risk classes from the SES and SOI risk adjusters and for some, the explanatory power has been taken over for about 100%. Policy makers could consider removing these classes from the model to reduce complexity without influencing selection incentives and predictive power. For the other subgroups it is important that the differences in financial results are assessed on how they influence selection incentives before big decisions can be made.

Contents

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1. Problem Analysis

In the Netherlands, every individual has a mandate to buy health insurance Health insurance gives people access to somatic care as well as mental health care, because of the health insurance act (Ministerie van Algemene Zaken, 2024). The health insurance act creates a competitive market for insurers. The competitive market means that insured individuals can switch insurers annually, which creates competition among insurers. Insurers can selectively contract healthcare providers, which creates competition among providers. Most of the time, these competitive markets are regulated. When these markets are not regulated, problems that arise are: premium differentiation, product differentiation and risk selection (McGuire & Van Kleef, 2018). To make sure these problems are avoided, a *regulated* competitive market has been set up in the Netherlands. The basics of these regulations are as followed: in the Netherlands there is a ban on premium differentiation, a standardized basic-benefits package and an acceptance duty for such basic coverage stated in the health insurance act (Richard et al., 2018).

Although the ban on premium differentiation helps achieve solidarity, it also has a disadvantage: it creates predictable profits on healthy individuals and predictable losses on unhealthy individuals (Jeurissen & Maarse, 2021). To compensate for the predictable profits and losses that result from the ban on premium differentiation, and to avoid risk selection, there is a risk equalization (RE) system. The RE system facilitates risk-adjusted transfers between insurers, essentially acting as a subsidy that redistributes funds from insurers with an overrepresentation of enrollees who have a low risk of making costs to insurers with an overrepresentation of enrollees who have a high risk of making costs (Van De Ven et al., 2022). Not only does the RE system compensate for the predictable losses, the RE system also counteracts incentives for insurers to engage in risk selection. Risk selection happens when insurers try to get more low-cost groups and less high-cost groups of enrollees. This means that people that have high costs are vulnerable to risk selection. Risk selection can lead to inequity in healthcare access, limited access to healthcare for and higher premiums for high-risk groups (van Kleef et al., 2018). When the incentives for risk selection are reduced by the RE system, the negative effects of risk selection are also avoided.

The RE system in the Netherlands is based on three models for three different types of care: somatic health care, mental health care and out-of-pocket payments due to the mandatory deductible (Ministerie van Volksgezondheid, Welzijn en Sport, 2024). The different models calculate the predicted costs per individual per year based on their risk profiles. These predicted costs per individual determine what the eventual payment for insurers is going to be. The risk profile of each enrollee is based on different risk adjusters. For the model based on mental care, the following risk adjusters are used in the RE system: age interacted with gender, zip-code clusters for mental care, source of income interacted with age, pharmacy- based cost groups for mental diseases, socioeconomic status interacted with age, household size interacted with age, high-cost groups for mental care, diagnoses-based cost groups for mental diseases and need-severity level (Ministerie van Volksgezondheid, Welzijn en Sport, 2024). The risk adjusters high-cost groups for mental care, diagnoses-based cost groups for mental diseases and need-severity level were added as risk adjusters later than the others. Each risk adjuster has different classes, and every enrollee is divided into these separate classes. Each class has its own payment weight and will determine the predicted cost of the individual (van Kleef et al., 2018).

A problem with the RE model right now is that the model is very complex. This complexity is a direct result of the big number of risk adjusters that are used and the amount of data on which these risk adjusters are based. Research shows that especially the risk adjusters' socio-economic status (SES) and source of income (SOI) both score highly on complexity (Ministerie van Volksgezondheid, Welzijn en Sport, 2023). Complexity may lead to confusion and has negative effects. Examples of the negative effects that complexity may have include: the difficulty in assessing the credibility of the model's outcomes and the increased need for precise rule application due to minor differences across years. Apart from that, the data collection for the RE models require significant resources, and it is easy to make errors in this process. The models complexity can have a negative effect on selection incentives, meaning that risk selection by health insurers is more likely to happen (Ministerie van Volksgezondheid, Welzijn en Sport, 2023).

Reducing the complexity of the RE model could be achieved by dropping risk adjusters that have the biggest impact on the complexity. Because of the big number of risk adjusters, and the fact other risk adjusters were added later, it could be possible that SES and SOI have less importance than they first had. The question, however, is what removing the risk adjusters SES and SOI would mean for the predictive power of the RE model and what influence the removal of these risk adjusters has on the selection incentives of subgroups who are vulnerable to risk selection. In this research, the goal is to find out if the risk adjusters SES and SOI are still relevant in the RE model and if they can be removed without increasing the selection incentives too much. In this study, the mental health model of the RE model will be researched. The main reason for limiting this study to the mental health model is to keep the research manageable given the limited time available for the thesis project.

Following the problem analysis, the following research question was formulated:

To what extent do the risk adjusters 'socioeconomic status' and 'source of income' contribute to the reduction of risk selection incentives for insurers in the risk equalization model for mental health care?

The goal of this study is to get an insight into what the risk adjusters 'socioeconomic status' and 'source of income' look like and how they overlap with other risk adjusters. The goal is to find out if how the risk adjusters SES and SOI influence selection incentives on their own, and how selection incentives are influenced when they are removed from the RE model. For this reason, the following secondary questions were set up:

1) *What do the risk adjusters 'socioeconomic status' and 'source of income' look like and what role have they played in the Dutch risk equalization model for mental care?*

2) *To what extent do the risk adjusters 'socioeconomic status' and 'source of income' compensate for predictable spending variation between relevant subgroups:*

a) in a risk equalization model for mental care without other risk adjusters?

b) in the current risk equalization model for mental care?

The first secondary question will be answered by conducting literary research on regulated competition, risk equalization and complexity. The second secondary question will be answered by simulating 4 different risk equalization models with an OLS regression and comparing the outcomes for selection incentives of these models.

Identifying relevant subgroups in this study means finding groups that are most vulnerable to risk selection. Identifying these groups and measuring their risk selection incentives is important for fully understanding the effect that the removal of SES and SOI has on risk selection. The overlap of the risk adjusters SOI and SES with the other risk adjusters in the model were analyzed by looking how well SOI and SES perform on their own and comparing that with the current risk equalization model.

The results of this study will give an elaborate overview of the risk adjusters SES and SOI and their influence on the predictive power and selection incentives of the mental health model of the RE system in the Netherlands. Not only can these results benefit the Dutch RE system, but they can also benefit other countries who make use of regulated competition and use a similar RE model. The study raises awareness about the complexity of RE models and provides a framework for assessing how the predictive power of an RE system is affected when SES and SOI are excluded from the mental health model. If these variables do prove to add value, other countries might consider incorporating them into their own models. Additionally, the study contributes by offering more insight into the mental health model, an area that has received less attention compared to the somatic model in previous research

In this thesis, a theoretical framework will be set up to give an understanding about how *regulated* competition and the Dutch risk equalization model works and the influences it has on risk selection. A broader understanding about the mental health model and its risk adjusters will be given with a separate focus on the socioeconomic status and source of income risk adjusters, thus giving the possibility to answer the first secondary question. Concluding the theoretical framework, different outcome measures for selection incentives will be discussed to give a sense on how risk selection is measured. Following the theoretical framework, the layout of the main analysis of this study will be explained and how this will give us answers to the second secondary questions in the methods section. After the methods section, the results of the analysis will be presented in the results section and at last the results will be discussed in the discussion and conclusion section.

2. Theoretical framework

In this section of this study, theoretical concepts and ideas will be discussed considering how *regulated* competition and risk equalization works in the Netherlands, together with international aspects of *regulated* competition. A broad overview of the Dutch risk equalization system will be given, together with a discussion on the aspects of complexity in the risk equalization models and their effect on risk selection. Finally, a summary will be given on how selection incentives can be measured in the context of a risk equalization model.

2.1 Regulated competition

A lot of health insurance systems in the world have a competitive market. This means that health insurers must compete on the price that they ask for their insurance and the quality of care they will give (Frank & Lamiraud, 2009). These competitive markets lead to health insurers wanting an equivalence between the money that they receive from the enrollees in the form of premium costs and the expected medical costs. In 2006, the Netherlands introduced the Health Insurance Act (*Zorgverzekeringswet*, Zvw), which is based on the principle of *regulated* competition.

Regulated competition in the Dutch health insurance means that multiple private insurers compete for customers, but the government regulates the market (Borkent et al., 2016). The competition arises because insurers can offer different premiums, additional services, and customer benefits, encouraging efficiency and quality improvements (Morrisey, 2001). The regulation is needed however to ensure that exclusion or excessive pricing is avoided. Problems that arise from the competition in a market without regulation are as follows: Premium differentiation per insurance product, product differentiation and risk selection (McGuire & Van Kleef, 2018). Premium differentiation means that insurers ask a different premium for the same insurance product for people who have a different risk profile. Product differentiation means that insurers change insurance products to attract lower risk groups and Risk selection means that high risk people are refused from getting insurance (Van Kleef, Eijkenaar, & Van Vliet, 2019). These negative effects created by the competitive market are resolved by regulation.

In the Netherlands, the following regulations are enforced by the government: a ban on premium differentiation, a standardized basic-benefits package to counter the product differentiation and an acceptance duty for insurers so that risk selection is not allowed. When comparing the *regulated* competition in the Netherlands with the regulation in other countries, a lot of similarities but also differences can be found. It is visible that in Europe, the competition is mainly focused on the individual level, whereas in the United States, the competition is mainly based on group level (employer-based competition) (McGuire & Van Kleef, 2018). The biggest differences can be found in how market regulations are set up. Differences can also be found in the health plan payment itself, whereas in some countries everyone has the same premium, in some countries people have different premiums and, in some countries, people don't pay premiums themselves, but premiums are paid via taxes (McGuire & Van Kleef, 2018).

2.2 Risk selection

The ban on premium differentiation that was discussed in the previous paragraph, gives insurers the incentive to try and attract more low-cost groups and less high-cost groups. This phenomenon is called risk selection (Van Kleef et al., 2013). Although an acceptance duty is enforced, meaning direct risk selection is legally prohibited, indirect selection strategies are still possible. For example, insurers can use directed advertising and marketing towards lower risk consumers by for example advertising on student platforms, sports apps, or social media pages related to fitness. These groups are statistically less likely to require expensive care, especially mental health services (Van Kleef & Van Vliet, 2025). This type of indirect selection is well-documented in the literature, which shows that insurers use marketing to attract profitable individuals and avoid high-risk individuals (Van De Ven et al., 2007). Another form of indirect risk selection is selectively contracting healthcare providers and offering them financial or non-financial incentives to manage their patient population in ways that indirectly discourage the treatment of high-risk patients. Providing supplementary insurances is also a way to induce indirect selection. By making supplementary insurances that mostly appeal to young and healthy people, insurers will most likely attract more young and healthy people who are more profitable than others. Most people take out their basic insurance and supplementary insurance with the same insurer, which makes the supplementary insurance an effective tool for engaging in risk selection (Van De Ven & Schut, 2009). Indirect risk selection most likely has the same consequences as direct risk selection: reduction of risk solidarity, reduction of efficiency, and reduction of quality of care.

A tool to avoid these negative effects of regulation is risk equalization. Risk equalization not only reduces the negative effects of risk selection but also removes the incentives for risk selection (Van Kleef et al., 2024). The RE system facilitates risk-adjusted transfers between insurers, essentially acting as a subsidy that redistributes funds from insurers with an overrepresentation of low-cost consumers to insurers with an overrepresentation of high-cost consumers (Withagen-Koster et al., 2024). The main goal is to neutralize predictable differences in healthcare costs that are created by variations in the risk profiles of patients. When the predictable differences in healthcare costs are neutralized, the incentive for indirect risk selection is reduced.

2.3 The Dutch risk equalization system

The Dutch risk equalization was introduced in 1993 *and* has 3 separate models: 1 for somatic health care, 1 for mental health care and 1 for out-of-pocket payments due to the mandatory deductible (McGuire & Van Kleef, 2018). Each model leads to a prediction of medical spending per individual per year. This predicted spending is the basis of the risk equalization payment (Van Kleef, Eijkenaar, & Van Vliet, 2019). At the beginning of each calendar year, insurers receive a payment based on the individual risk profile of each insured individual. The risk profile of each individual is defined by several risk adjusters. A risk adjuster is a category that influences the medical spending of a person. Every risk adjuster has different classes, and every enrollee is divided into these separate classes. Each class has its own payment weight and will determine the predicted cost of the individual. (McGuire & Van Kleef, 2018). The risk adjusters used in the mental health care model and the separate classes are shown in Table 1:

Table 1. Risk adjusters of mental health care RE model 2025 and their description

Risk adjuster	Brief description	Year of introduction
Age interacted with gender	30 classes of age groups interacted with gender	2008
Zip-code clusters for mental care	10 clusters of four-digit zip codes based on a specific set of regional characteristics	2008
Source of income interacted with age (SOI)	30 classes based on source of income interacted with age	2008
Pharmacy-based cost groups for mental diseases (FKG)	10 classes based on the use of specific pharmaceuticals in the previous year	2008
Diagnosed-based cost groups for mental diseases (DKG)	17 classes based on mental diagnoses in the previous year	2008
Socioeconomic status interacted with age (SES)	8 classes based on the level of household income interacted with age	2008
High-cost groups for mental care (GGZ-MHK)	8 classes based on mental health care spending of the last 5 years	2012
Household size interacted with age (PPA)	17 classes based on people living per household interacted with age and classes based on long-term care (Wlz) use interacted with age.	2014

For a complete overview of all risk adjusters and their classes see Ministerie van Volksgezondheid, Welzijn en Sport (2024). As shown in Table 1, not all risk adjusters have been included in the mental health model since the beginning. The risk adjusters high-cost groups for mental care (GGZ-MHK) and Household size interacted with age were added later. Risk adjusters can be added anytime to improve the predictive power of the model if proven valuable.

2.4 Risk adjusters: Source of income and Socioeconomic status

In this research, the risk adjusters SOI interacted with age and SES interacted with age will be studied. The reason for this is because these risk adjusters contribute the most towards complexity in the RE system (Ministerie van Volksgezondheid, Welzijn en Sport, 2023). To get a full understanding on how these risk adjusters contribute to this complexity, a brief description on how these risk adjusters look like will be given: The risk adjuster SOI is interacted with age is divided in 7 subgroups all interacted with 2-6 different groups of age. The 7 different subgroups are: completely disabled, partly disabled, social security beneficiaries, students, fully self-employed, high educational degree, and other (including employed). The 7 subgroups interacted with age gives 30 classes in total. The risk adjuster socioeconomic status is also interacted with age and is divided in 4 subgroups. The subgroups are based on income per household and give the following subgroups: Very low SES, low SES, medium SES and high SES. These subgroups are interacted with 2 different groups of age and give a total of 8 classes (Ministerie van Volksgezondheid, Welzijn en Sport, 2024).

Over time, the risk equalization model has grown more complex by adding new risk adjusters and new categories for these risk adjusters (McGuire & Van Kleef, 2018). While this can enhance the predictive power of the RE system, and therefore reduce incentives for risk selection, it also brings a lot of new data and complexity with it. Research that was conducted in 2023 by the Dutch Ministry of Health, Welfare and Sport describes what kind of elements of complexity are present in a RE system and it shows which risk adjusters increase the complexity of the model through these elements. The elements that are described are: Substantive coherence with other classes, a risk adjuster consists of many classes, the model is unstable due to policy changes, there are individual steps that are complex to execute, many different steps in the feature derivation and multiple data years. It is shown that SES and SOI add complexity through almost all these aspects. (Ministerie van Volksgezondheid, Welzijn en Sport, 2023).

Challenges that arise from the growing complexity of the RE system include difficulties in checking whether the model outcomes make sense. Applying of the rules correctly is becoming harder because of (sometimes small) differences between the data from different years. There is also a risk that the complexity could lead to unexpected and unwanted effects, such as problems with incentives for risk selection, efficiency, fair competition, and appropriate care, because these effects are becoming harder to understand (Ministerie van Volksgezondheid, Welzijn en Sport, 2023). Complexity reduction in risk equalization models can improve efficiency, interpretability, and implementation. Examples of how complexity can be reduced are: Risk adjuster selection, categorization of variables, and reduction of disease categories. Risk adjuster selection means only using the risk adjusters that have a valuable impact on the predictive power.

2.5 Estimation of payment weights and calculation of RE payments

An important part of the risk equalization model are the payment weights. Every class of every risk adjuster has its own payment weight. A payment weight is a numerical value that represents the expected additional (or lower) healthcare cost associated with a specific class of a risk adjuster (Layton et al., 2018).

For the estimation of the payment weights, data on individual healthcare costs, demographics, and morbidity indicators is collected. The data used is from the most recent year for which all claims have been finalized. For the 2025 risk equalization year, cost data from 2022 is therefore used, along with insured characteristics from 2017 through 2022. Using this data, individuals are categorized into the various risk adjuster classes based on characteristics such as age, gender, socioeconomic status, and medical diagnoses (Layton et al., 2018). A restricted OLS regression model is used to estimate the expected healthcare costs for each risk class, this is done separately for the somatic, mental and deductible model (Ministerie van Volksgezondheid, Welzijn en Sport, 2024). The “restriction” means that the predicted costs at the individual level must be greater than zero euros (Quickonomics, 2024). The estimated coefficients are interpreted as weights representing the average expected spending of individuals in each group.

Using these payment weights, the total predicted costs can be estimated by calculating the sum of the somatic care and mental health care model, minus the adjustment for the deductible model. Using the total predicted costs, the total risk equalization payment is determined by removing the flat-rate premium from the predicted costs, except for individuals under 18, for who the payment equals the full predicted costs (Layton et al., 2018).

2.6 Measures of the selection incentives

The evaluation of risk adjustment models is typically based on several key criteria, such as those outlined in the WOR 1130 assessment framework (Van Kleef, Van Vliet, Oskam, & Panturu, 2023). The criteria mentioned in the WOR 1130 are: Predictive power and selection incentives, Efficiency incentive, Manageable complexity and Validity and measurability. Predictive power and selection incentives show to what extent the model fairly distributes financial risks among health insurers. Efficiency incentive is the incentive for insurers to promote efficiency and quality in healthcare. Manageable complexity stands for the feasibility of implementing the model without excessive administrative burden. And finally, validity and measurability show the reliability and verifiability of the data and assumptions used.

These criteria help assess the effectiveness and fairness of the model in distributing healthcare costs. In this study, the focus is on the criteria: predictive power and incentives for risk selection. Predictive power refers to how well the model predicts variations in healthcare costs. Common measures for this are the R^2 statistic and the Cumming’s Prediction Measure (CPM). R^2 indicates the proportion of the variance in the dependent variable that is explained by the model. It is a measure of the explained variance. The CPM indicates the proportion of the absolute differences in the dependent variable that is explained by the model. So, unlike the R^2, CPM is based on absolute errors rather than squared errors (W. P. M. M. Van De Ven & Van Kleef, 2024).

Incentives for risk selection are assessed by examining the so-called *financial results*. The financial result is the over/under compensation that insurers get in euros for different subgroups in euros, particularly for groups who have higher costs and higher health risks (Eijkenaar & Van Vliet, 2017). The higher the over/under compensation, the higher the incentives for risk selection. Consumers who have a high amount of overcompensation, are profitable for insurers and they will try to attract more of these individuals, leading to more risk selection. Consumers who have a high amount of under compensation, are unprofitable for insurers and the insurers will try to avoid these individuals (Van Kleef, Eijkenaar, & Van Vliet, 2019). By calculating the financial result on select subgroups, policymakers can not only detect if there is an incentive for risk selection, but also where this incentive is located.

3. Methods

To answer the research question, a quantitative simulation was conducted with STATA to assess the added value of the risk adjusters ‘socioeconomic status’ and ‘source of income’. The added value was assessed by comparing risk incentives in different RE models for specific subgroups. The outcome measure for the risk incentives will be over/under compensation, or in other words, the financial result. Specific subgroups considering chronic mental health conditions, SES classes and SOI classes with high mean costs were selected for the analysis. The financial results for the subgroups of a model without RE were compared with a model where only the risk adjusters SES and SOI were used, and the financial result of the specific subgroups of the current RE model were compared with the current RE model where SES and SOI were excluded. In the following chapter, the data sources that were used for the analysis will be discussed, the framework of the main analysis of this thesis will be explained more broadly and a validity and reliability analysis will be conducted.

3.1 Data

The main data source that was used is the Nivel Primary Care Database. The Nivel Primary Care Database (Nivel Zorgregistraties Eerste Lijn) collects everyday data from healthcare providers, such as general practitioners, to keep track of people’s health and how often they use healthcare services. The data is based on a sample that reflects the Dutch population and contains microdata of approximately 1.2 million patients in the Netherlands (Nivel, 2025). The dataset makes use of the ICPC system to code and classify medical conditions. The ICPC codes describes what medical condition a person has and whether its chronic or not. The supervisor has supplemented this data file with the information needed to estimate the 2025 RE model. This dataset relates to the costs and characteristics of individuals insured under the Dutch Health Insurance Act (Zvw) in 2022.Each row in the dataset represents an individual patient, and key variables include age, gender, diagnosis codes and the risk adjuster classes. With this dataset, subgroups of the year 2021 will be examined. The reason for looking at subgroups based on the previous year is to look at the ***predictable*** profits and losses.

With this dataset, the 2025 RE model was replicated and examined to assess the impact of the RE model on selection incentives for subgroups based on specific mental disorders. To make the Nivel Primary Care Database representable for the entire Dutch population, every observation has been given a weight. These weights have been determined in previous research and are shown in the evaluation of risk equalization 2024 & 2025 (Van Kleef & Van Vliet, 2025). Every analysis in this research has been weighted to make it representable. The data was used to simulate the risk adjustment model, determine the predicted costs for each insured individual and identify interesting subgroups for the evaluation of risk adjustment models. An exploratory data analysis was conducted to examine the distribution of key variables such as age, gender, chronic condition status, mental health diagnoses, number of observations and average costs.

3.2 Data analysis

After the data was received, several steps were taken to analyze the data and run different simulations of the current risk equalization model. For that reason, this study consisted of 5 separate steps: 1) data preparation, 2) exploratory data analysis and OLS regression analysis, 3) identifying subgroups and 4) calculation of under/overpayment and 5) comparing the under/overpayments between populations and subgroups. In the following paragraph, these steps will be further explained step by step.

3.2.1 Step 1 - Data preparation

Firstly, based on the available dataset, an analysis dataset was created by removing any unnecessary variables and linking the patient data to the additional data that includes predicted cost estimations for individuals based on their medical history, along with additional socio-economic factors necessary for the 2025 RE model. The complete data analysis was conducted in STATA. Separate variables were created to sort individuals into different groups. These groups were based on gender, age, socioeconomic status, source of income, people with at least one chronic mental disease and separate groups for al the mental chronic diseases.

3.2.2 Step 2 - Exploratory data analysis OLS Regression analysis

After the data was prepared, an exploratory data analysis was performed to give an overview of the data. The exploratory data analysis was weighted. Variables that were considered for the exploratory data analysis were: Age, gender, number of observations, weighted number of observations and the percentage of people with at least one chronic mental disorder.

For the main analysis, an OLS regression was used. The OLS regression estimates the average relationship between the risk adjusters and the outcome (mental health cost). For the real estimation of the models, a restricted OLS regression analysis should have been conducted. But considering the limited time and the complexity of this type of regression, a normal OLS regression will be used in this thesis. With the OLS regression, four weighted risk equalization models were simulated in STATA as shown in Table 2.

Table 2. Risk equalization models simulated

Model	Description
M0	No RE, the predicted costs for individual *i* are equal to the average costs in the population.
M1	RE with only adjusters SES and SOI, the predicted costs for individual *i* are equal to the predicted costs according to an OLS model with SES and SOI classes as explanatory variables.
M2	Current RE model, the predicted costs for individual *i* are equal to the predicted costs according to an OLS model with all current risk adjuster classes as explanatory variables.
M3	Current RE model without SES and SOI, the predicted costs for individual *i* are equal to the predicted costs according to an OLS model without SES and SOI classes as explanatory variables.

In model M1, only the main classes of SES and SOI were included in the regression model to make sure the effect of age is avoided. Including the interaction with age in this model would result in partly capturing the effect of age, while we are only interested in SES and SOI.

The regression models made a prediction of the healthcare costs $\hat{Y}_i$ per insured individual over the risk adjuster classes that were in used in the regression. To assess the predictive power of each of the models, measures like R² and Cummings prediction method were calculated. The formula that was used for the R² is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2}$$

And the formula that was used for the CPM:

$$CPM = 1 - \frac{\sum_{i=1}^{n}|Y_i - \hat{Y}_i|}{\sum_{i=1}^{n}|Y_i - \bar{Y}_i|}$$

These show how well the models explain differences in healthcare costs between individuals where the R² indicates what portion of the variance in costs is explained by the models and the CPM indicates what portion of the absolute differences in costs is explained by the models. The R^2 and the CPM can be used to find the added value of SES and SOI for the overall predictive power of the models. This was done by comparing the difference in R^2 and CPM between model M1 and M0 with the difference in R^2 and CPM between model M3 and model M2. The difference of model M1 with model M0 show how well the risk adjusters function on their own and the difference of model M3 with model M2 show the added value of the risk adjusters in the current model.

3.2.3 Step 3 - Subgroup identification

Based on these simulations, relevant subgroups were identified to help during the evaluation of the different models. Relevant subgroups were based on different chronic mental health diagnoses, socioeconomic status and source of income. The mean actual mental health costs of these groups were derived from the OLS regression together with the percentage of the population.

One of the most important factors for subgroup analysis is the diagnoses of the individuals in the dataset, particularly those related to chronic mental health conditions. The subgroups are derived from conditions observed in 2021, after which over- or under compensation is assessed for the year 2022. This is a common approach in risk adjustment research, as the focus lies on identifying predictable profits and losses. Different diagnoses often correlate with varying healthcare needs and costs. Therefore, evaluating how well the different risk equalization models account for these differences will be crucial for assessing the model's effectiveness. Subgroups based on socioeconomic status and source of income are also interesting, because they may become subject to risk selection when the risk adjusters are removed from the models.

3.2.4 Step 4 - Calculating financial results

After this, the difference between the predicted costs $\hat{Y}_i$ and the actual costs Y_i were derived from the 4 separate models for all the subgroups that were selected in step 3. With the predicted and actual costs, the financial result for subgroup g was calculated using the following formula:

$$\text{Financial result for subgroup g} = \frac{\sum_{i \in g}(\widehat{Y_i} - Y_i)}{n_g}$$

The financial results were calculated for all the different subgroups for every model. The financial results were put next to each other in a graph to give a visual overview of the data. This was done separately for the groups with the chronic mental illnesses, the SES classes and the SOI classes.

3.2.5 Step 5 - Comparison of Financial results between models and subgroups

With the calculations of step 4, the financial results of the different models were compared for the different subgroups. The financial results for the different subgroups of M0 were compared with the financial results for the different subgroups of M1. A t-test was run to show if differences were statistically significant. The results of the comparison of M0 with M1 will show what the potential added value of SES and SOI is on selection incentives. The financial mean differences are the potential added benefit of SES and SOI. After this, the financial results for the different subgroups of M2 were compared to the financial results for the different subgroups of M3. Also, for this comparison, a t-test was run to show if differences were statistically significant. The results of the comparison of M2 with M3 shows how the removal of SES and SOI influence the selection incentives. The financial mean differences are the actual added benefit of SES and SOI. The difference between the potential added benefit and actual benefit shows how much of the predictive power has been taken over by other risk adjusters and how much is left. Using the potential added benefit and actual added benefit of SES and SOI, the percentage of how much predictive power that has been taken over by other risk adjusters was calculated.

3.3 Validity & reliability

To ensure validity, this study was carefully designed to align with research methods that are used in practice. The main goal was to assess the added value of SES and SOI as risk adjusters in the Dutch risk equalization model. By using the same method for simulating the models and using the same outcome measures as is used in practice, validity is ensured. The data that was used in this research is the Nivel Primary Care Database set that contains the medical information of about 1.2 million patients in the Netherlands. By using a weight for every observation in the dataset, the data was made representable for the entire Dutch population. Research shows that the dataset is highly suitable for scientific research and is frequently used in health policy studies (Nivel, 2023). Another reason why the data is reliable, is that it is the data that is also used in practice to make predictions on the Dutch RE models. The reliability of the analysis was strengthened by using standardized and repeatable procedures.

While the design ensures a high degree of internal consistency and relevance, certain limitations exist. Instead of a restricted OLS regression, a normal OLS regression was used (Van Kleef et al., 2016). As said before, this is done because of the limited time and the complexity of the restricted OLS regression.

This research not only has a relevance in the Netherlands but can also be important for other countries. The results of this study may be interesting to other countries with risk equalization systems. However, specific results cannot be directly translated to other countries due to differences in healthcare systems, populations, and risk equalization mechanisms.

4. Results

In this section, the results of the quantitative simulations conducted to evaluate the added value of the risk adjusters SES and SOI within the Dutch RE model for mental health care will be presented. First, a descriptive overview of the dataset is provided, including patient characteristics and cost distributions. Next, the outcomes of the OLS regression models (M0–M3) are presented, focusing on key statistical performance measures such as R^2 and the Cumming's Prediction Measure (CPM). After this, the financial results are analyzed by comparing the predicted and actual costs for the selected subgroups. The financial results of model M0 are compared with the financial results of model M1, and the financial results of model M2 are compared with the financial results of model M3. Finally, differences financial results are evaluated.

4.1 Descriptive statistics

Firstly, an exploratory data analysis was conducted to give us an overview of the given data set. The results of the exploratory data analysis are shown in Table 3 and contain information about the sample size, mean cost, percentage of men and women per age category and the percentage of people with at least one chronic mental disorder.

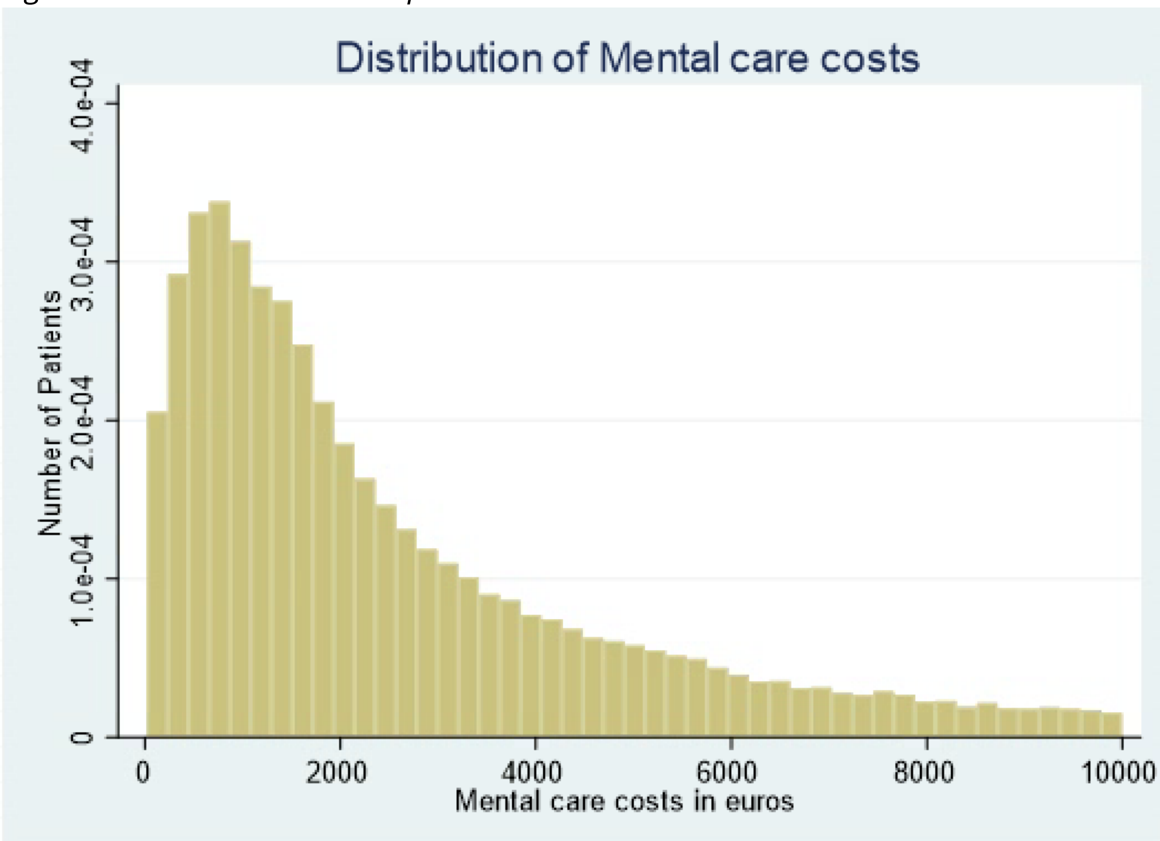
Table 3. Descriptive statistics of the sample

Number of observations			1,184,748
Weighted number of observations			14,044,432
Mean cost (in euro's)			344.04
% Men			
19-34			13.3
35-44			7.4
45-54			8.2
55-64			8.6
65+			11.8
% Women			
19-34			13
35-44			7.4
45-54			8.3
55-64			8.6
65+			13.5
% People with at least one chronic mental disorder			4.3

Based on the Nivel dataset, weighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Chronic mental disorders that were included: Schizophrenia, disability due to mental illness, dementia (including Alzheimer's disease), mental retardation and personality disorder.

As seen from Table 3, the size of the Nivel Primary Care Database contains microdata of 1.184.748 patients. When using the weight, this leads to a weighted number of observations of 14.044.432. The average mean mental healthcare cost per person is 344,04 euros. It is seen in the table that the women to men ratio is almost 1 : 1, with the biggest age group being women and men between the age of 19 and 34. Also shown in Table 3 is that around 18,4 % of the sample population has at least one or more chronic mental disorders.

Figure 1. Cost distributions of patients with cost > 1 and <10000 euros



Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432.

In figure 1, it is shown how the costs are distributed among the population of the Nivel Primary Care Database. To make sure that the figure is understandable, only patients who have costs between 1 and 10000 euros are shown. The big majority of the patients in the dataset have a total cost of 0. The weighted amount of observations that had a cost of 0 euros was 13.2 million. For this reason, these patients are excluded from this figure. The figure shows that most patients that have a health care cost above 0 euros, have mental health care costs between 0 and 2000.

4.2 Regression analysis

Following the regression analysis of the 4 RE models, the data as shown in Table 4 was obtained. Shown in Table 4 is the mean predicted costs for ever regression model together with the R2 and the CPM.

Table 4. Data obtained by regression analysis of M0, M1, M2 and M3

Model:	Mean predicted Costs:	R2	CPM
M0	344.04	0	0
M1	344.04	0.0181	0.052
M2	344.04	0.2567	0.302
M3	344.04	0.2556	0.301

Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432.

In this study, we evaluated the predictive performance of two risk equalization models using both the R^2 and the Cumming's Prediction Measure (CPM). These outcomes provide insight into how well the models predict individual healthcare costs. M0 showing a R^2 of 0 and a CPM of 0 was expected, because M0 is the model without RE. M1 shows a R2 of 0,0181, which means that M1 explains only 2 percent of the variation in mental healthcare costs between individuals. The CPM of 0.052 suggests that the model reduces the average absolute prediction error by 5 percent compared to a naive model that simply predicts the average cost for everyone. M2 gives a R^2 of 0.2567 and M3 gives a R^2 of 0,2556, which means that M2 and M3 both explain around 26% of the variation in individual costs. The CPM of 0.302 from model M2 and the CPM of 0.301 from model M3 suggests that the model reduces the average absolute prediction error by 30 percent compared to a naive model for both the models. To find the added value of SES and SOI, a comparison can be made between the R^2 and CPM of model M1 and M3 with model M2. It is seen that the difference between the R^2 and CPM is much smaller between M3 and M2 when compared to M1, which means that the added value of SES and SOI is smaller in M3 than in M1.

4.3 Subgroup identification

For the subgroup identification, the 5 chronic mental disorders together with patients who have at least 1 chronic mental disorder were deemed as a possible subgroup, as well as all 4 of the SES risk adjuster classes and all the SOI risk adjuster classes. Shown in Table 5 are the percentages of the total population together with the mean actual mental healthcare costs. Every group from the chronic mental disorders, except patients with dementia had higher mean mental health costs than the average population. Patients with dementia had an average mean cost of 212 euros, which is lower than the average population. Patients with schizophrenia are the patients with the highest mental health care costs with an amount of 8791 euros. 22,04% of the population are the patients with a very low SES and are the only subgroup from the SES subgroups that have a higher mean mental healthcare cost than the average population with a mean cost of 729 euros. Considering the SOI groups, the subgroups with AVI, AO, patients receiving social assistance and students had a higher mean cost than the average population. The patients receiving social assistance had the highest mean cost of the SOI subgroups with an average mean mental healthcare cost of 1521.

Table 5. Possible subgroups and specifications

Potential subgroup:	% of total	Mean actual costs (in euros)
Patients with 1 chronic mental disorder or more	4.3	1925
Schizophrenia	0.3	8791
Disability due to mentall illness	0.1	862
Dementia, includig alzheimer's disease	0.8	212
Mental retardation	0.7	1142
Personality disorder	1.6	2725
Patients with very low SES	22.04	729
Patients with low SES	19.49	310
Patients with medium SES	29.25	219
Patients with high SES	29.22	202
Patients with IVA	0.2	544
Patients with AO	1.8	1611
Patients receiving social assistance	3.5	1521
Patients who are students	4.7	431
Patients who are self-employed	3	223
Patients with higher education	7.4	277
Patient in the referencegroup	18.2	327

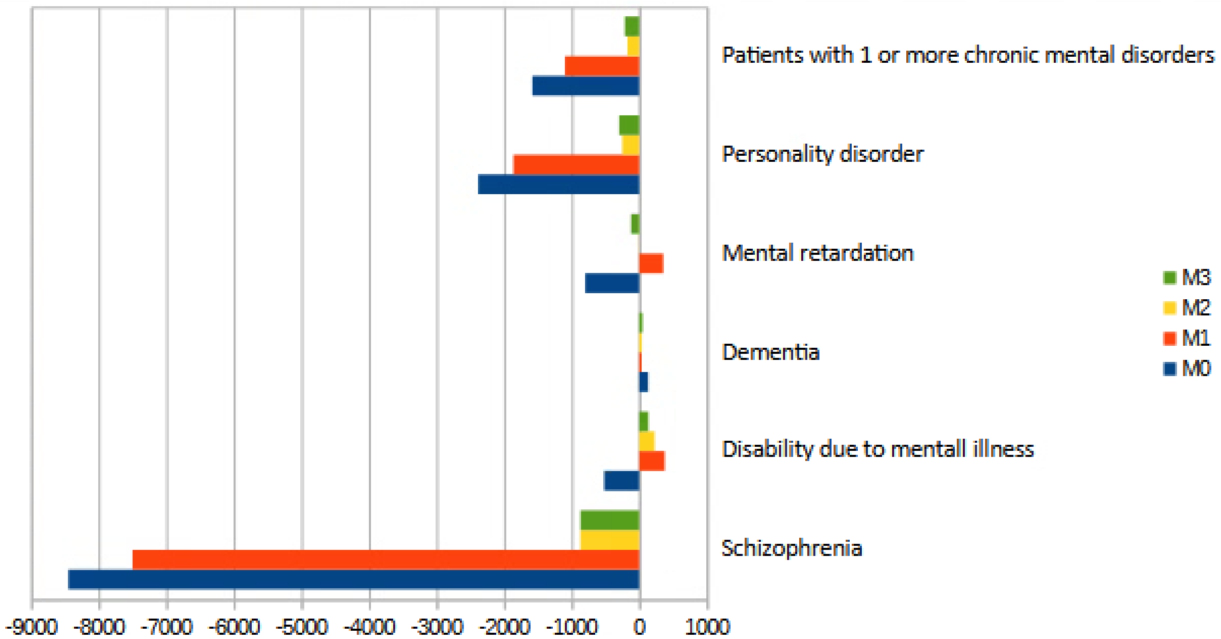
Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432. SES stands for Socio-economic status, AO for 'Arbeidsongeschiktheid' being the partly disabled group and IVA for 'Inkomensvoorziening volledig arbeidsongeschikten' being the completely disabled group.

All explored subgroups shown in Table 5 were included in the final financial result analysis.

4.4 Financial results

After completing the subgroup identification, the results of the regression analysis for all four models were collected for every separate subgroup. With the formula as given in the methods chapter, the financial result for separate subgroups were calculated for all 4 models. Financial results from the different subgroups were put next to each other giving figure 2 and 3. Figure 2 show us the subgroups from the mental disorders and the financial result for each model. Figure 3 shows us the subgroups from the SES classes and Figure 4 shows the subgroups from the SOI classes and the financial result for each model.

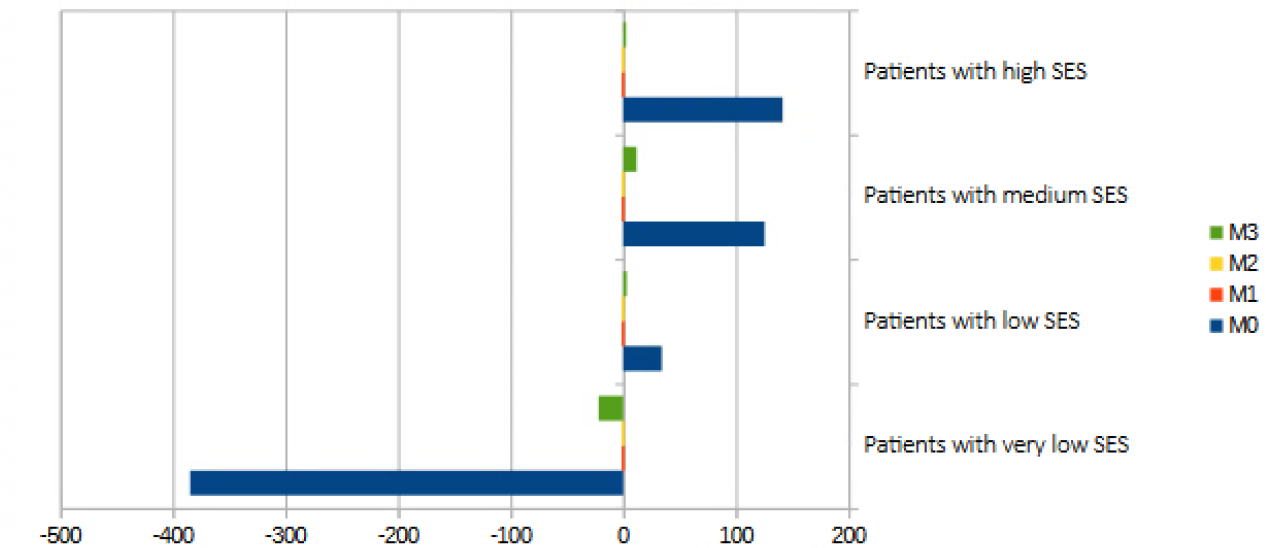
Figure 2. Financial Results for mental disorders subgroups from model M0 to M3.



Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432. Subgroups are based on data from 2021, and the predicted financial results are based on 2022.

As shown in Figure 2, patients with schizophrenia, personality disorders and patients with 1 or more chronic mental disorders, have a negative financial result for all the four models. Patients with mental retardation have a positive financial result for model M1 and patients with a disability due to mental illnesss have a positive financial result for model M1, M2 and M3. Patients with dementia have a small but positive financial result for all four of the models. These subgroups are therefore overcompensated in these models. Patients with schizophrenia have the largest negative financial results for all four models, which means they are undercompensated the most. These patients have an undercompensation of 8447 euros in model M0, 7496 euros in model M1, 870 euros in model M2 and 869 euros in model M3.

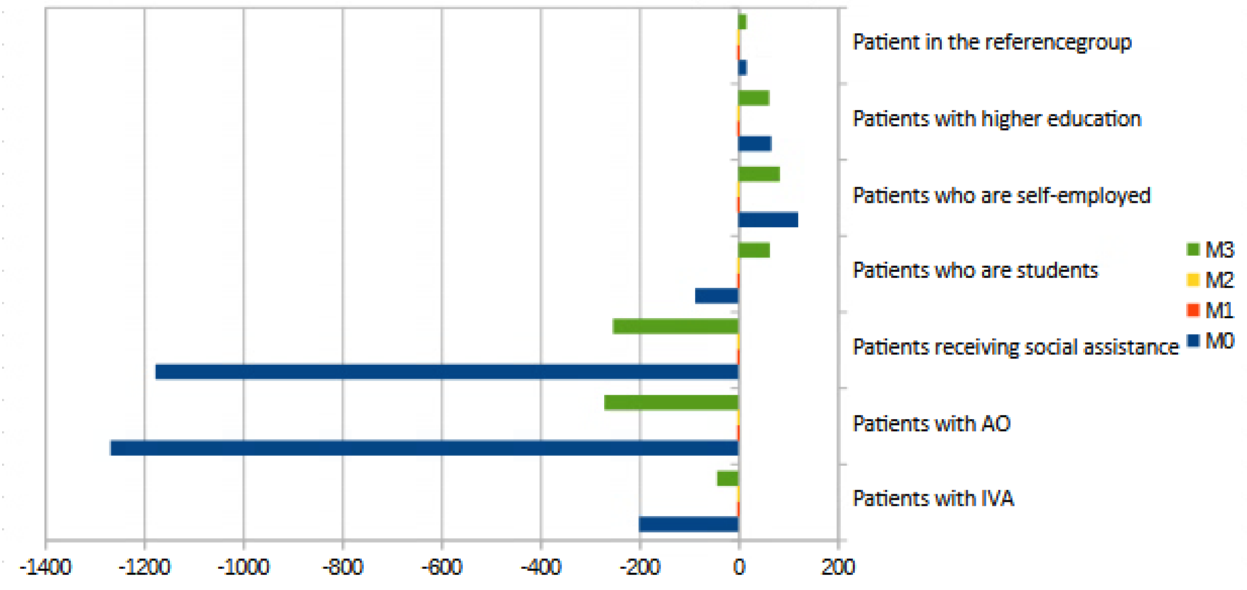
Figure 3. Financial Results for SES subgroups from model M0 to M3.



Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432. SES stands for Socio-economic status.

As seen in Figure 3, only patients with very low SES have a negative financial result for model M0 and M3, the biggest negative result coming from model M0 with a financial result of -385 euros. This means that they have the biggest incentive for risk selection among these SES classes when no risk adjusters are used. The other 3 classes give positive financial results for all models with M0 from patients with high SES giving the highest financial result with 141 euros. The financial results of model M1 and M2 are all 0. This is because these classes are directly adjusted for by the SES and SOI risk adjusters in the models.

Figure 4. Financial results for SOI subgroups from model M0 to M3.



Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432. AO stands for 'Arbeidsongeschiktheid' being the partly disabled group and IVA stands for 'Inkomensvoorziening volledig arbeidsongeschikten' being the completely disabled group.

Figure 4 shows the financial results for the SOI subgroups. Patients in the reference group, with higher education and who are self-employed have positive financial results for all models with self-employed patients having the biggest positive financial result of 120 euros in model M0. These groups also have positive financial results in model M3, meaning that they are overcompensated when SES and SOI are taken away and are profitable for health insurers. Patients who are students have a positive financial result in M3 and a negative financial result in M0. The rest of the subgroups have a negative financial result with patients with AO having the biggest negative financial result with an under-compensation of 1267 euros in model M0 and an undercompensation of 270 euros in model M3. This means that they have the biggest incentive for risk selection among these SOI subgroups. Just as in Figure 3, The financial results of model M1 and M2 are all 0. This is also because these subgroups are directly adjusted for by the SES and SOI risk adjusters in the models.

4.5 Comparison of Financial results

Following the analysis of the financial results, a t-test was conducted to compare the financial results of the different models and look for a statistically significant difference. Model 1 was compared with model 0 and model 3 was compared with model 2. In Table 6, the mean difference of the financial result is shown in euros rounded up to full numbers, where the financial result of model 1 was subtracted from model 0. In Table 7 the mean difference of the financial result is shown where the financial result of model 2 was subtracted from model 3. The mean difference of financial result was shown for all selected subgroups together with the standard deviation, as well as the 95% confidence interval together with the p-value. Shown in Table 8 is the potential and actual added benefit together with the percentage of predictive power that is taken over by other risk adjusters.

Table 6. Mean difference of financial results of subgroups between M0 and M1

	Mean difference Financial result	Std. Dev.	95% Conf. Interval		P-value
Schizophrenia	947	266	917	976	< 0.05
Disability due to mental illness	827	1049	768	886	< 0.05
Dementia	-107	162	-110	-103	< 0.05
Mental retardation	1120	1063	1093	1146	< 0.05
Personality disorder	522	902	508	535	< 0.05
Patients with 1 Chronic mental disorder or more	230	602	227	232	< 0.05
Patients with very low SES	359	669	356	361	< 0.05
Patients with low SES	-29	394	-31	-28	< 0.05
Patients with medium SES	-122	313	-122	-120	< 0.05
Patients with high SES	-131	279	-132	-130	< 0.05
Patients with IVA	190	468	172	207	< 0.05
Patients with AO	1239	1058	1223	1254	< 0.05
Patients who are students	108	124	107	109	< 0.05
Patients receiving social assistance	1307	1067	1297	1317	< 0.05
Patients who are self-employed	-109	131	-110	-107	< 0.05
Patients with higher education	-58	92	-59	-57	< 0.05
Patients in the referencegroup	37	175	36	38	< 0.05

Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432. SES stands for Socio-economic status, AO for 'Arbeidsongeschiktheid' being the partly disabled group and IVA for 'Inkomensvoorziening volledig arbeidsongeschikten' being the completely disabled group.

Table 6 shows the mean difference of financial results between model M0 and M1 for all the subgroups. These differences in financial results are the potential added value of

SES and SOI. As seen in Table 6, the mean differences for patients with schizophrenia, Disability due to mental illness, mental retardation, personality disorder, with 1 chronic mental disorder or more, very low SES, IVA, AO, students, who receive social assistance and who are in the reference group are higher than 0, which means that model 0 gives a higher financial result when compared to model 1 for every subgroup. The subgroup with the biggest mean difference of financial result are the patients receiving social assistance with a mean difference of 1307 euros. This means that SES and SOI risk adjusters have the biggest potential added value for this group when looking at selection incentives. The group with the lowest mean difference of financial result are the patients with low SES with a financial result of -29 euros. The p-value being lower than 0.05 for all the mean differences of financial results shows us that the differences that is found between model M0 and M1 are statistically significantly bigger than 0.

Table 7. Mean difference of financial results of subgroups between M2 and M3

	Mean difference financial result	Std. Dev.	95% Conf. Interval		p-value
Schizophrenia	0	266	-9	9	0.98
Disability due to mental illness	91	302	74	108	< 0.05
Dementia	-9	54	-10	-8	< 0.05
Mental retardation	130	329	122	138	< 0.05
Personality disorder	44	240	41	48	< 0.05
Patients with 1 Chronic mental disorder or more	9	187	9	10	< 0.05
Patients with very low SES	18	206	17	18	< 0.05
Patients with low SES	-5	102	-5	-4	< 0.05
Patients with medium SES	-13	78	-13	-12	< 0.05
Patients with high SES	-2	75	-3	-2	< 0.05
Patients with IVA	47	74	44	50	< 0.05
Patients with AO	272	322	267	277	< 0.05
Patients who are students	-63	27	-63	-63	< 0.05
Patients receiving social assistance	312	454	308	317	< 0.05
Patients who are self-employed	-84	33	-85	-84	< 0.05
Patients with higher education	-63	34	-63	-63	< 0.05
Patients in the referencegroup	-19	32	-19	-19	< 0.05

Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432. SES stands for Socio-economic status, AO for 'Arbeidsongeschiktheid' being the partly disabled group and IVA for 'Inkomensvoorziening volledig arbeidsongeschikten' being the completely disabled group.

Table 7 shows the result of the comparison of financial results between model M2 and Model M3 for all the subgroups. The results shown in this table are the actual added value of SES and SOI. As seen in the table, the mean difference of financial results between for patients with Schizophrenia was 0 euros, with a p-value of 0.98 showing us that the mean difference is not statistically different from 0. The other subgroups do show a statistically significant difference in mean financial results with a p-value that's lower than 0,05 for all other subgroups. The same subgroups as in Table 6 show a positive mean difference in financial results, except for the patients who are students and who are in the reference group. This means that the under compensation is bigger in model M3 than in model M2 for these subgroups. Patients receiving social assistance have the biggest mean difference in financial results with 312 euros. The other mean differences in financial results have a range from -84 to 272.

Table 8. Comparison of potential and actual added benefit of SES and SOI

	Potential added benefit	Actual added benefit	Percentage taken over by other risk adjusters
Schizophrenia	947	0	100
Disability due to mental illness	827	91	89
Dementia	-107	-9	92
Mental retardation	1120	130	88
Personality disorder	522	44	92
Patients with 1 Chronic mental disorder or more	230	9	96
Patients with very low SES	359	18	95
Patients with low SES	-29	-5	83
Patients with medium SES	-122	-13	89
Patients with high SES	-131	-2	98
Patients with IVA	190	47	75
Patients with AO	1239	272	78
Patients who are students	108	-63	158
Patients receiving social assistance	1307	312	76
Patients who are self-employed	-109	-84	23
Patients with higher education	-58	-63	-9
Patients in the referencegroup	37	-19	151

Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432. SES stands for Socio-economic status, AO for 'Arbeidsongeschiktheid' being the partly disabled group and IVA for 'Inkomensvoorziening volledig arbeidsongeschikten' being the completely disabled group.

When comparing the potential added value of SES and SOI with the actual added value of SES and SOI, it is shown to what extent the other risk adjusters have taken over the explanatory power of SES and SOI. Shown in Table 8 is the potential and actual added benefit together with the percentage of explanatory power that is taken over by other risk adjusters. It is seen that the explanatory power of SES and SOI have been completely taken over for patients with schizophrenia since the actual added benefit is 0. The percentage of explanatory power that is taken over by other risk adjusters averages around 90 percent with patients who are self-employed being the lowest with a percentage of 23 percent.

5. Conclusion and Discussion

In this concluding chapter of this thesis, the key findings of this study will be put in relation to the original research questions and objectives. A summary of the main findings will be given, and the strengths and limitations of this study will be discussed, together with policy implications and directions for other research. Finally, the main conclusion will be given.

5.1 Summary of main findings

The main goal of this study was to find out to what extent the risk adjusters 'socioeconomic status' and 'source of income' contribute to the reduction of risk selection incentives for insurers in the risk equalization model for mental health care. This was done by firstly looking at what the risk adjusters 'socioeconomic status' and 'source of income' look like and what role they play in the Dutch risk equalization model for mental care. Then secondly by looking at to what extent the risk adjusters 'socioeconomic status' and 'source of income' compensate for predictable spending variation between relevant subgroups. This was done by setting up different risk equalization models with different risk adjusters and calculating the financial results for separate relevant subgroups so that the risk selection incentive could be determined.

To find out what the risk adjusters 'socioeconomic status' and 'source of income' look like and what role they play in the Dutch risk equalization model for mental care, a theoretical framework was set up. The risk adjuster SOI interacted with age is divided in 7 subgroups all interacted with 2-6 different groups of age. The 7 different subgroups are: completely disabled, partly disabled, social security beneficiaries, students, fully self-employed, high educational degree, and other (including employed). These subgroups interacted with 2-6 different groups of age gives a total of 30 classes. The SES risk adjuster is interacted with age and is divided in 4 subgroups all interacted with 2 different groups of age. The 4 subgroups are based on total income of a household an account for 8 classes in total. Both risk adjusters were added in the year 2008 and research shows that they both contribute to bigger complexity in the RE model (Ministerie van Volksgezondheid, Welzijn en Sport, 2023).

For the data analysis, The Nivel Primary Care Database was used. Following the regression analysis of the 4 simulated models, the same mean predicted costs were found which was 344.04 euros. and a R^2 ranging from 0 to 0.2567 and a CPM ranging from 0 to 0.302 between the 4 models. The CPM and R^2 were slightly better in model M2 when compared to model M3, but the differences are so small that the predictive power of the models will be the same.

For the subgroup analysis, subgroups considering chronic mental diseases, SES and SOI were included. After the relevant subgroups were determined, the financial results of the subgroups were calculated for all four models. Patients with schizophrenia, personality disorders, who have 1 or more chronic mental disorders, a very low SES, IVA, AO and receiving social assistance have a negative financial result for all the four models, meaning that they are always undercompensated. This under compensation is an incentive for risk selection.

The potential added benefit is the added benefit of SES and SOI in a risk equalization model for mental care without other risk adjusters and had a financial result that ranged from -131 to 1307 euros. This means that the risk adjusters SES and SOI reduce the selection incentives of the subgroups from -131 to 1307 euros when they work without any other risk adjuster and when compared to a naïve model with no risk adjusters. The actual added benefit is the added benefit of SES and SOI in the current risk equalization model for mental care and had a financial result that ranged from -84 to 312. When comparing the potential added benefit of SES and SOI with the actual added value of SES and SOI to see what percentage of explanatory power has been taken over by other risk adjusters, it is seen that for most subgroups the explanatory power has almost completely been taken over by other risk adjusters.

5.2 Strengths, limitations and directions for future research

It is important to recognize the strengths and limitations of this thesis to contextualize the findings and suggest directions for future research. A major strength of this thesis is that the methods that were used in this thesis are almost identical to the methods that are used in practice. For this reason, the findings are relevant and reliable.

The only difference between the methods from this thesis and the methods used in practice is that instead of a restricted OLS regression, a normal OLS regression was used. This was done because of the limited time and the complexity of the restricted OLS regression. Because a normal OLS was used, some predictions may deviate from the real estimation that would be done in practice. Given in the appendix is an overview with the predicted mental healthcare cost per subgroup when a normal OLS regression and when a restricted OLS regression is used. Many subgroups show little to no difference, while other groups show a bigger difference.

For this reason, it could be interesting in future research to use restricted OLS regressions when more time is at hand to make the results even more representable. Nevertheless, for the purpose of this study and answering the research question the findings are still deemed reliable and representable. Another part that was not researched in this thesis but is important for policy implications, is to find out how differences in financial results affect selection incentives and to see if the differences found in this study affect the selection incentives. It would be important for policy decisions to have a framework on how differences in financial results could affect the way insurers try to perform risk selection and have a guideline considering these decisions.

5.3 Policy implications

The findings of this thesis have implications for policymaking in the Dutch risk equalization model for mental healthcare. The main results considering the financial results and potential/actual added benefit of SES and SOI show us how selection incentives are influenced by SES and SOI and what percentage of explanatory is taken over by other risk adjusters. The results show that the predictive power of a model without the risk adjusters SES and SOI is almost the same to a model with these risk adjusters, but potential added benefits and factual added benefits of SES and SOI vary between subgroups.

Taking this difference into account, a decision on whether to include something does not necessarily have to be made at the level of SES and/or SOI. The decision can also be made at the level of risk classes within SES and SOI. For risk classes with a limited actual contribution, it could be considered to remove them. Risk classes with a ‘sufficient’ actual contribution could be retained. When applied to the results of this thesis, it could be considered to remove the risk class of patients with a very low SES and of patients with a high SES. The percentages of explanatory power being taken over by other risk adjusters are almost 100 for these classes. For these classes, we are almost certain that SES and SOI have a limited actual contribution and can be taken out of the model.

For the other classes, research must be done on how and if these differences in financial results affect selection incentives and to what level the contribution is deemed ‘sufficient’. If these differences are assessed, policymakers could consider removing these risk classes of SES and SOI from the RE model as well to reduce the complexity of the model.

5.4 Overall conclusion

To give an overall conclusion of this thesis, the results show that the risk adjusters SES and SOI compensate for predictable spending variation between relevant subgroups with a mean difference in financial results ranging from -131 to 1307 euros in a risk equalization model for mental care without other risk adjusters and a mean difference in financial results ranging from -84 to 312 euro in the current risk equalization model for mental care. Comparing the potential and actual added benefit of SES and SOI shows that when SES and SOI are taken out of the model, the explanatory power is taken over by other risk adjusters for 90% on average. For the risk classes where almost 100% of the explanatory power has been taken over, it is likely that removing them will have no or only minimal effect on the selection incentives. For the other risk classes and subgroups, the differences in financial result need to be assessed on how this could impact the RE system for mental healthcare, policymakers could consider removing the risk adjusters SES and SOI from the RE model to reduce the complexity of the model.

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Appendix

Table 9. Mean predicted cost from normal OLS compare to restricted OLS regression.

	Mean predicted cost with normal OLS	Mean predicted cost with restricted OLS	Absolute difference
Schizophrenia	7921	7924	3
Disability due to mental illness	1091	1281	190
Dementia	455	251	204
Mental retardation	1136	1455	319
Personality disorder	2475	2421	54
Patients with 1 Chronic mental disorder or more	1751	1820	69
			0
Patients with very low SES	728	767	39
Patients with low SES	310	290	20
Patients with medium SES	218	207	11
Patients with high SES	202	193	9
			0
Patients with IVA	544	569	25
Patients with AO	1611	1648	37
Patients who are students	431	408	23
Patients receiving social assistance	1520	1452	68
Patients who are self-employed	223	232	9
Patients with higher education	277	277	0
Patients in the referencegroup	327	314	13
Whole population	344	343	1

Based on the Nivel dataset, reweighted to reflect the 2022 population covered under the Dutch Health Insurance Act (Zvw), aged 18 and older. Weighted number of observations: 14,044,432. SES stands for Socio-economic status, AO for 'Arbeidsongeschiktheid' being the partly disabled group and IVA for 'Inkomensvoorziening volledig arbeidsongeschikten' being the completely disabled group.