

**Balancing complexity and performance of the Dutch risk
equalization model:
evaluation of the risk adjusters ‘Socioeconomic status’
and ‘Source of income’**

Iris Seinen (734571)
Supervisor: dr. R.C. van Kleef
Co-reader: dr. S. Kent
Rotterdam
Date: 18-06-2025
Word count: 14441

Abstract

The Dutch health insurance system is based on regulated competition, and risk equalization is a key element of this. The risk equalization model compensates insurers for predictable profits and losses associated with expected healthcare costs. Over the years, the Dutch risk equalization model has evolved into a sophisticated model. However, due to continuously adding risk adjusters, the complexity of the risk equalization model increased which threatens its feasibility. Since socioeconomic status (SES) and source of income (SOI) have been identified as complex risk adjusters, this thesis evaluates their contribution in terms of explanatory power and reduction of selection incentives.

Using microdata from the Nivel Primary Care Database (NIVEL-PCD) and a risk equalization dataset that contains individual-level data on medical spending and information on all risk adjusters for 2022, four risk equalization models were simulated. Due to these simulations, the potential and net contribution of SES and SOI to the explanatory power, as well as evaluation of mean financial results for specific subgroups based on chronic conditions and on SES and SOI classes was assessed.

The findings demonstrate that the contribution of SES and SOI to reducing predictable profits and losses is limited for most subgroups. Notably, for individuals in lower SES and SOI classes, these risk adjusters still play a role in counteracting selection incentives. However, for most subgroups, other risk adjusters in the risk equalization model already capture a large portion of the potential contribution that SES and SOI could provide.

Policymakers may face a trade-off between complexity and selection incentives. Since SES and SOI contribute to reducing selection incentives for vulnerable subgroups, policymakers could consider retaining certain specific risk classes of SES and SOI rather than excluding the entire risk adjuster from the risk equalization model.

Table of contents

Acknowledgement	4
1. Problem analysis	5
2. Objective and research question	6
3. Theoretical framework	7
3.1 Regulated competition	7
3.2 Risk selection and insurer actions to selection incentives	7
3.3 The role of risk equalization	8
3.4 Risk adjusters in the risk equalization model of 2025	9
3.5 Estimation of payment weights and calculation of RE payment	11
3.6 Measures of the performance of risk equalization models	12
3.7 Complexity and performance of the risk adjusters SES and SOI	13
4. Methods	16
4.1 Data	16
4.2 Data analysis	17
4.2.1 Step 1: Simulation of the risk equalization model	18
4.2.2 Step 2: Identification of relevant subgroups	19
4.2.3 Step 3: Calculation of the mean financial result of relevant subgroups	19
4.2.4 Step 4: Comparison of the potential and net contribution of SES and SOI in reducing selection incentives	19
4.3 Validity & reliability	20
5. Results	21
5.1 Explanatory power	21
5.2 Identification of subgroups	22
5.3 Contribution of SES and SOI to the reduction of selection incentives	24
5.3.1 Subgroups based on the presence of a chronic condition	25
5.3.2 Subgroups based on specific chronic conditions	26
5.3.3 Subgroups based on socioeconomic status	28
5.3.4 Subgroups based on source of income	30
5.4 Comparison of the potential and net contribution of SES and SOI	32
6. Conclusion and discussion	34
6.1 Summary of findings	34
6.2 Strengths, limitations and directions for future research	35
6.3 Policy implications	36
6.4 Overall conclusion	38
7. Reference list	39
8. Appendix 1	42
9. Appendix 2	43

Acknowledgement

This thesis was written for completing the Master's program in Health Economics, Policy and Law at the Erasmus University in Rotterdam. I would like to thank the following individuals and institutions for their support and contributions.

First, I would like to sincerely thank my supervisor, Dr. Richard van Kleef, for his valuable guidance throughout the entire process. The regular meetings and feedback moments have significantly contributed to the final result and made the thesis writing process more structured and manageable.

Next, I am grateful to the Dutch Ministry of Health, Welfare and Sports and the Association of Health Insurers for access to (anonymized) claims data. I am also grateful to the Netherlands Institute for Health Services Research (NIVEL) for access to morbidity information registered by general practitioners. This study has been approved according to the governance code of Nivel Primary Care Database, under number NZR-00322.052. The use of electronic health records for research purposes is allowed under certain conditions. When these conditions are fulfilled, neither obtaining informed consent from patients nor approval by a medical ethics committee is obligatory for this type of observational studies containing no directly identifiable data (art. 24 GDPR Implementation Act jo art. 9.2 sub j GDPR).

Lastly, I would like to thank my fellow students for the brainstorming sessions we shared throughout the past months. I am also thankful to my family and friends for their continued support and encouragement.

1. Problem analysis

The Dutch health insurance system is based on Enthoven's principles of regulated competition (Enthoven, 1988; Van de Ven et al., 2013). In this type of market, consumers can freely choose their insurer, and insurers can freely contract care providers. This creates competition among insurers and among care providers (Van de Ven et al., 2013). To prevent market failure, the government regulates competition through community rating per insurance plan, open enrolment, mandatory basic health insurance, a standardized care package and risk equalization. The goal of the government is to protect the societal goals of accessibility, affordability, and quality of care.

An important principle of regulated competition is that insurers are not allowed to risk-rate their premiums. This means that the premium a health insurer charges for its health insurance plan must be the same for all individuals. Therefore, insurers are not allowed to charge higher premiums to individuals with higher expected healthcare costs. This ensures solidarity within the Dutch healthcare system, but at the same time, this creates selection incentives for insurers. To address this, risk equalization is implemented to compensate insurers for the predictable expected costs of an individual. A well-functioning risk equalization system is essential to counteract incentives for risk selection and to ensure a level playing field among insurers.

Since the implementation of the Dutch risk equalization system in 1993, various risk adjusters have been gradually added to the model. Over the years, the Dutch risk equalization system has evolved into a sophisticated model that includes demographic, socioeconomic and morbidity-based risk adjusters (Van Kleef et al., 2019). However, continuously adding risk adjusters has increased the complexity of the risk equalization model (Hamstra et al., 2023). The National Health Care Institute is concerned about this increasing complexity, which threatens the feasibility of the risk equalization model. Every year, changes are implemented to ensure that the model performs better in predicting individuals' health spending. However, most of these adjustments increase the complexity of the risk equalization model (Hamstra et al., 2023).

The increasing complexity of the model raises concerns about transparency, (data) reliability, effectiveness, and the validity of risk adjusters (WOR 1234). Transparency is important in the decision-making process around risk equalization. A lack of transparency raises concerns about the reliability of the risk equalization model (PricewaterhouseCoopers Advisory N.V., 2006). Furthermore, complexity increases the risk of incorrect calculations, along with the risk that these remain undetected (WOR 1234). The complexity of the model leads to higher (administrative) costs regarding data collection and calculations (McGuire et al., 2021). Moreover, research and implementation are hindered by time constraints, which pose a risk to the continuity of the model (WOR 1234). Additionally, as the risk equalization model becomes more complex, fewer individuals may fully understand the model, which reduces its feasibility (PricewaterhouseCoopers Advisory N.V., 2006).

Previous research by Hamstra et al. (2023) identified several aspects of risk adjusters that contribute to the complexity of the risk equalization model. In that study, the risk adjusters 'socioeconomic status (SES)' and 'source of income (SOI)' were identified as complex. Therefore, removing SES and SOI would substantially reduce the complexity of the model. However, it is unclear how this would affect the performance of the risk equalization model, particularly in terms of predictive power and selection incentives. It is possible that the performance of the risk equalization model does not change significantly, since over the years many other risk adjusters have been added to the model. Therefore, this thesis examines the

impact on the performance when the risk adjusters SES and SOI are excluded from the Dutch risk equalization model for somatic care¹.

2. Objective and research question

This thesis evaluates the impact of the risk adjusters SES and SOI on the performance of the Dutch risk equalization model for somatic care. Therefore, the research question is:

To what extent do the risk adjusters ‘socioeconomic status’ and ‘source of income’ contribute to the performance of the Dutch risk equalization model for somatic care?

To answer this question, several sub-questions are formulated. Sub-question 2 distinguishes between two versions of the Dutch risk equalization system to examine how SES and SOI overlap with other risk adjusters.

Sub-question 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 somatic care?

Sub-question 2: To what extent do the risk adjusters ‘socioeconomic status’ and ‘source of income’ compensate for predictable spending variation between relevant subgroups:

2a: In a risk equalization model for somatic care without other risk adjusters?

2b: In the current risk equalization model for somatic care?

This research may contribute to the improvement of the Dutch risk equalization model. If SES and SOI significantly impact the model’s performance, it might be advisable to retain these risk adjusters. If these risk adjusters do not significantly impact the performance of the risk equalization model, the regulators could consider excluding SES and SOI, which would reduce the complexity of the risk equalization model. The findings of this study provide valuable insights for other countries with similar risk equalization models, as these findings might help them to make well-informed decisions regarding the inclusion of socioeconomic risk adjusters.

This thesis is structured as follows. The next chapter outlines the theoretical framework, which explains the core principles of the Dutch risk equalization model for somatic care. Sub-question 1 is addressed in this chapter by reviewing existing literature and policy documents. The following chapter describes the methodology of this thesis which is a quantitative simulation study using microdata. Then, the results of this simulation study are presented, which provides the information to answer sub-question 2. The thesis concludes with a summary of the main findings and a discussion.

¹ The Dutch risk equalization model consists of two separate models: one for mental health care (GGZ) and one for somatic care. This thesis focuses on the risk equalization model for somatic care.

3. Theoretical framework

This section explains the core principles of the Dutch risk equalization model for somatic care. First, regulated competition in the healthcare market is described. Then, risk selection and the role of risk equalization in the healthcare market are explained, followed by a description of the risk equalization model with a focus on SES and SOI. Lastly, measures for evaluating the performance of the risk equalization model and the performance of SES and SOI are described.

3.1 Regulated competition

Regulated competition is an approach to structure the healthcare market in a country. Besides the Netherlands, several other countries such as the United States, Belgium, Germany, Israel, Ireland, and Switzerland have based their healthcare markets on the principles of regulated competition (McGuire and Van Kleeef., 2018). This type of market combines market competition with government regulation to prevent market failure. The Dutch health insurance system became regulated with the introduction of the Health Insurance Act in 2006. This act mandates that all residents must obtain basic health insurance from private insurers. In the healthcare market, there is competition among insurers and among healthcare providers. Consumers can freely choose their health insurer, which creates competition among insurers. In addition, insurers selectively contract care providers, which creates competition among healthcare providers (Enthoven, 1993; Van de Ven et al., 2013). In the Health Insurance Act, the government has an important role in structuring and managing the health insurance market. Regulatory tools to prevent market failure include the regulation of coverage (e.g., standardized benefit packages), regulation of enrolment (e.g., open enrolment), management of market entry (e.g., screening of provider networks), market support and surveillance (e.g., monitoring of risk selection), and regulation of insurance plan payment (e.g., risk equalization) (McGuire and Van Kleeef., 2018). In addition, insurers have an acceptance obligation, which means that insurers must accept all applicants who enrol for a basic health insurance. Another regulatory tool is that insurers are not allowed to risk-rate their premiums. This means that the premium a health insurer charges for its health insurance plan must be the same for all individuals, which promotes solidarity within the healthcare system. However, an important disadvantage is that insurers then face unpriced risk heterogeneity, which creates incentives for risk selection.

3.2 Risk selection and insurer actions to selection incentives

Risk selection is defined by Newhouse as ‘actions by consumers and insurers to exploit unpriced risk heterogeneity and break pooling arrangements’ (Newhouse, 1996). If incentives for risk selection are present, insurers seek to attract low-risk individuals (low healthcare costs) because these individuals are predictably profitable. At the same time, insurers want to exclude high-risk individuals (high healthcare costs) due to the predictable losses from these individuals. An insurer who has relatively more low-risk individuals in their portfolio can charge a lower premium compared to insurers who have relatively more high-risk individuals in their portfolio. This creates an unequal playing field among insurers and threatens the fairness and efficiency of the healthcare system (Van de Ven & Ellis, 2000). Therefore, risk equalization is necessary to counteract incentives for risk selection.

The existing risk equalization model does not perfectly compensate the insurers for the predicted medical spending per individual (Withagen-Koster et al., 2022; Van Kleeef et al., 2019). As a result, there are still incentives for risk selection. Insurers can respond to these incentives through various actions, described as “insurer actions”, which entail all measures that seek to attract low-risk individuals and exclude high-risk individuals (Van Kleeef et al., 2019). In the Dutch

health insurance market, there are several types of insurer actions possible (Van Kleef et al., 2019; Van Kleef et al., 2024). First, insurers can make their insurance plans unattractive for high-risk individuals through selective contracting. This is possible since insurers can freely decide which providers they contract with and under what conditions. Insurers can avoid contracting providers who provide high-quality care for specific diseases. In this way, the patient access to these providers decreases, which lowers the level of playing field for providers. In addition, through selective contracting, the coverage of the insurance product differs from patient preferences (Van Kleef et al., 2019; Van Kleef et al., 2024). Another possible action by insurers is cost-sharing. An insurer can charge copayments for out-of-network care, which will influence consumer choices. Furthermore, insurers can manage healthcare use by actively steering patients in choosing a preferred and cost-effective provider (Van Kleef et al. 2019). Insurers can also deter high-risk individuals by lowering the quality of their customer service by, for example, not answering phone calls or emails, or by being impolite to high-risk individuals (Bauhoff, 2012). Additionally, insurers have the freedom in designing their advertising and marketing strategies. Insurers can target specific, profitable subgroups through selective advertising (Van Kleef et al., 2019). Most often, consumers take both basic and supplementary health insurance from the same insurance company (Duijmelinck & Van de Ven, 2014). Therefore, insurers can charge excessive premiums for supplementary health insurance products to deter unprofitable subgroups from purchasing the basic health insurance (Van Kleef et al., 2019).

All in all, risk selection is a threat to the solidarity and efficiency of the healthcare system. These actions by insurers as a reaction to selection incentives, emphasize the importance of risk equalization in ensuring accessible, affordable, and effective healthcare for the entire population. How successful the above-mentioned insurer actions are in breaking the pooling arrangement, depends on the response of consumers. The response of consumers depends on multiple factors such as consumers attitude toward risk, price sensitivity, knowledge of the healthcare system, and the estimation of healthcare costs incurred by consumers (Van Kleef et al., 2024; Van Kleef et al., 2019).

3.3 The role of risk equalization

The goal of risk equalization is to counteract incentives for risk selection and to ensure an equal playing field among insurers. This makes risk equalization a key element of Enthoven's principles of regulated competition (Enthoven, 1988; Van de Ven et al., 2013). Therefore, all countries with healthcare systems based on regulated competition also use risk equalization (McGuire and Van Kleef, 2018). For each insured individual, the risk equalization model estimates the expected healthcare costs based on risk characteristics of the insured. The insurer then receives financial compensation for the predicted medical spending of the insured. If an insurer has relatively more high-risk individuals, who tend to have high healthcare costs, the insurer receives more subsidies from the risk equalization fund. An example of high-risk individuals is the elderly, who tend to have higher healthcare costs than younger, low-risk, individuals. An insurer will then receive a higher payment for those elderly individuals compared to younger individuals. In a perfectly functioning risk equalization system, health insurers have no incentives for risk selection, as there are no predictable profits and losses on groups of insured remaining. Therefore, risk equalization is necessary to create an equal playing field for insurers and to counteract incentives for risk selection (Ministerie van VWS, 2017).

Insured individuals are classified into categories based on different risk adjusters, as described in paragraph 3.4. The risk equalization model in the Netherlands functions as an ex-ante system. This means that insurers receive a prospective payment for each of their insured based on the risk characteristics of the insured. Since it is a prospective payment, the insurers bear financial

risk, which provides incentives for efficiency (Van Kleef et al., 2018). When insurers manage to lower healthcare costs, for example, by negotiating lower prices with healthcare providers or by organizing care more efficiently, they realize savings and efficiency gains, which are profitable for insurers. However, this was not always the case. In the early years of the Dutch risk equalization system, when the performance of the risk equalization model was still limited, insurers bore little to no financial risk. During this period, cost-based compensation was used. This type of risk sharing protects insurers from excessive financial losses by providing payments based on actual healthcare costs of an individual (Van Kleef et al. 2022). However, as the risk equalization system developed and became more sophisticated, the risk sharing mechanism was gradually reduced. This increased the financial risk borne by insurers, and nowadays, insurers bear nearly the full financial risk for all healthcare expenses (Van Kleef et al., 2018). This highlights the importance of reducing selection incentives for insurers.

3.4 Risk adjusters in the risk equalization model of 2025

Since the introduction of the Dutch risk equalization model in 1993, various risk adjusters have been gradually added. This resulted in the current risk equalization model, which consists of thirteen different risk adjusters (Ministerie van VWS, 2024). These risk adjusters are: age interacted with gender, pharmacy-based cost groups (PCGs), diagnosis-based cost groups (DCGs), socioeconomic status (SES) interacted with age, region, source of income interacted with age, household size interacted with age, multiple-year high cost (MYHC), physiotherapy diagnosis groups (PDGs), prior-year spending for home care, historical somatic morbidity (HSM), an indicator for pregnancy and delivery, and non-residents. A short description of these risk adjusters is provided in Table 1. A more detailed explanation can be found in the *Regeling risicoverevening 2025 (concept)*, Staatscourant, NR.31526 (Ministerie van VWS, 2024).

Table 1: Description of the risk adjusters used in the risk equalization model for somatic care in 2025 (Van Kleef et al., 2018; Ministerie van VWS, 2024)

Risk adjuster	Number of classes ^a	Description
Age interacted with gender	42 (whereas 21 classes for men and 21 classes for women)	For both men and women, the age classes are: 0 year born in t, 0 year born in t-1, 1-4 year, 5-9 year, 10-14 year, 15-17 year, 5-year cohorts up to age 90, and 90+ year.
Pharmacy-based cost groups (PCGs)	48 + 1	PCGs are based on prior prescription drug use. Individuals are classified in one or more categories if they used a predefined number of specific pharmaceuticals in the previous year.
Diagnosis-based cost groups (DCGs)	26 + 1	Clusters for specific inpatient and outpatient diagnoses from the previous year. The clustering is based on the highest residual spending. Individuals can be classified in multiple DCGs.
Socioeconomic status (SES) interacted with age	12	Four SES classes interacted with three age groups. Classification is based on the total household income. The SES classes are based on income distribution (lowest 20%, middle 20-40%, middle 40-70%, top 30%). These SES classes are interacted with age groups 0-17, 18-69, and 70+ year.
Region	10	Clusters based on the four digits of the zip code. Zip codes are clustered based on expected spending given a certain set of regional characteristics.
Source of income interacted with age	36	Based on source of income or education in interaction with six age groups. The categories are completely unable to work, partly unable to work, social assistance beneficiaries, students aged 18 to 34, self-employed individuals, highly educated individuals aged 18 to 44, reference group, and individuals aged 70+ years.
Household size interacted with age	18	Based on the number of residents per street address. The categories are: long-term care institution with treatment (permanent), long-term care institution with treatment (newly admitted), long-term care institution without treatment or extramural long-term care (permanent), long-term care institution without treatment or extramural long-term care (newly admitted), single-person household, and a category with other individuals not classified in one of the categories above. Each category is interacted with three age groups (18-69, 70-79, and 80+ years). Individuals aged 0-17 form a separate class.
Multiple-year high-cost groups (MHCGs)	8 + 1	Based on high healthcare spending in the past three years. It is assumed that individuals with a chronic condition have multiple high year costs.
Physiotherapy diagnosis cost groups (PDCGs)	4 + 1	Clusters based on diagnoses from physiotherapy visits in the previous year. Individuals can only be classified in one PDCG.
Prior-year spending for home care	9 + 1	Based on home care spending in the previous year. The classes are distinguished as the top 0.25%, 0.5%, 1.0%, 1.5%, 2.0% and bottom 97.5%.
Historical somatic morbidity (HSM)	1 + 1	Individuals who were classified in at least one somatic morbidity category in year t-3.
Indicator for pregnancy and delivery	3 + 1	Classification based on pregnancy. The three groups are: pregnant in year t but not giving birth in year t, gave birth in year t and pregnancy started in year t-1, gave birth in year t and pregnancy started in year t.
Non-residents	3	Classification for non-resident individuals. The three groups are: individuals residing in the Netherlands (residents), seasonal workers, and other insured persons residing abroad.

^a+1 represents the reference category. Consists of individuals who are not classified in any of the other classes, they are classified in a separate class.

The risk adjuster ‘socioeconomic status’ in interaction with age was added in 2008 and is based on the total household income. The classification is based on income distribution and individuals are classified into one of four SES classes. The lowest 20% of the income distribution is classified as very low. From 20-40% of the distribution is classified as low, 40-70% is classified as middle, and the top 30% is classified as high. Each of these groups is interacted with three age groups (0-17, 18-69 and 70+ years) (Van Kleef et al., 2018; Ministerie van VWS, 2024). This results in twelve different classes. Individuals who live in a long-term care institution are classified in the SES class very low. Individuals classified in a lower SES class tend to have higher healthcare expenses compared to individuals classified in a higher SES class (Ministerie van VWS, 2017).

The risk adjuster ‘source of income’ interacted with age was added in 1995 and was the third risk adjuster added to the model. The National Healthcare Institute classifies individuals between ages 18 and 64 into one of the following categories: completely unable to work, partly unable to work, social assistance beneficiaries, students aged 18 to 34, self-employed individuals, highly educated individuals aged 18 to 44, and individuals aged 70+ (Ministerie van VWS, 2024). Other individuals not classified in one of these categories, together with unemployed individuals, form the reference group. Individuals can only be placed in one category. If an individual can be placed in multiple categories, they are categorized into the first one in which they qualify, following the order of categories as described above (Ministerie van VWS, 2024). Each of these categories, including the reference group, is interacted with six age groups (0-17, 18-34, 35-44, 45-54, 55-64, 65-69). An exception is made for students, which only have two age groups (0-17 and 18-34) and for highly educated individuals, which have three age groups (0-17, 18-34, 35-44). Individuals aged 0-17 are classified based on the classification of the adults living at the same address. If multiple adults are living at that address, the classification follows the same order as the categories described above. Individuals aged 65-69 are classified based on their most recent classification prior to their 65th birthday. Individuals aged 70+ form a separate group, as this group is largely retired and is explicitly adjusted through the risk adjuster age. Individuals classified as completely unable to work, partly unable to work, or social assistance beneficiaries tend to have higher healthcare expenses compared to individuals classified in the other classes (Ministerie van VWS, 2017).

3.5 Estimation of payment weights and calculation of RE payment

Each year, a payment weight is estimated for every risk class within the risk equalization model. The height of the payment weight for a specific risk adjuster in year t is derived using an individual-level regression of medical spending from year $t-3$ on that risk adjuster. For the entire population, data is available from year $t-3$ about the medical spending and risk characteristics of the insured. This data from year $t-3$ is then used to estimate the payment weight of risk adjusters for year t . To make year $t-3$ data is representative for year t , two adjustments are needed. First, the data from year $t-3$ is reweighted, which means that the number of enrollees in each risk class is adjusted to reflect the expected prevalence for year t . Second, the data from year $t-3$ is corrected for system changes and cost inflation between year $t-3$ and year t (Van Kleef et al., 2018). After these adjustments, a constrained regression model is used to estimate the coefficients of the different risk adjusters. Constrained regression is a form of least-squares regression but imposes specific restrictions on the estimated payment weights. The derived coefficients represent the payment weights, and a separate payment weight is derived for each class within a risk adjuster.

For each insured, the healthcare costs are predicted based on the risk characteristics of an insured using the risk adjusters and these payment weights. For individuals who were enrolled

for only part of the year, for example due to death, the predicted healthcare costs are annualized (Van Kleef et al., 2018). However, insurers do not receive these predicted healthcare costs on a one-to-one basis, since insured individuals aged 18 and over are subject to a mandatory out-of-pocket payment and they pay a premium. To account for this, the government determines a fixed amount p , which insurers must finance through their income from premiums. For each insured, the equalization payment is based on the predicted healthcare costs minus the fixed amount p . For individuals under the age of 18, who do not pay premiums or out-of-pocket costs, the risk equalization payment equals the predicted healthcare costs (Van Kleef et al., 2018). The National Healthcare Institute provides these equalization payments from the risk equalization fund to the insurers.

3.6 Measures of the performance of risk equalization models

Empirical literature shows that there are different opinions about the goal of the risk equalization model, which complicates the evaluation of the model (Stam et al., 2021.; Van de Ven et al., 2023). Having a clear goal about risk equalization is important for policymakers and researchers to identify relevant evaluation criteria. An important element of the goal of risk equalization is to remove predictable profits from the low-risk individuals and predictable losses from the high-risk individuals, so that selection incentives no longer persist. However, there are debates about whether efficiency should be an element of the goal of risk equalization as well, since an improvement in the performance of the risk equalization model often has both positive and negative effects on efficiency (Van Kleef et al., 2024). Improving the risk equalization model increases efficiency by creating a level playing field for insurers and by reducing selection incentives. This is, for example, due to the fact that insurers focus more on improving quality instead of focusing on selection activities. On the other hand, improving the risk equalization model has a negative effect on efficiency since there are increased incentives for gaming and insurers might focus less on prevention and cost-efficiency since they will be compensated for the costs anyway. In addition, improving the risk equalization model increases the complexity of the model. Therefore, policymakers and researchers face complex trade-offs when improving and evaluating the performance of the risk equalization model (Van de Ven et al., 2023.; Van Kleef et al., 2024).

In the Netherlands, each year, a group of experts (WOR) evaluates the performance of the risk equalization model. They examine factors such as incentives for risk selection, incentives for efficiency, complexity, and the validity and measurability of the model (WOR 1234). Previous research commissioned by the National Health Care Institute has indicated that the complexity of the model hinders its implementation and complicates the understanding of changes when focusing on efficiency (Hamstra et al., 2023). As a result, insurers place less emphasis on improving care and instead focus more on attracting low-risk individuals, as they are overcompensated. This study will focus on the contribution of SES and SOI to the statistical performance of the model and to the extent SES and SOI contribute to reducing selection incentives.

In the literature, several measures are distinguished for evaluating the performance of the risk equalization model (Van Kleef et al., 2024). There are measures for the overall performance such as the R-squared (R^2), Cumming's Prediction Measure (CPM) and the Mean Absolute Prediction Error (MAPE). These ex-ante measures assess the statistical performance in terms of the explanatory power of the risk equalization model and indicate the extent to which predicted costs correspond to actual costs. Most often, the R^2 is used when evaluating the statistical power of the risk equalization model (Layton et al., 2017). In the Netherlands, the R^2 is reported in all evaluation projects since the introduction of the risk equalization model in 1993. In recent

years, the R^2 of the risk equalization model has been slightly above 0.3. (Van Kleef et al., 2018). The CPM and the MAPE have been used in evaluation projects since 2015. All these statistical measures are informative in measuring the predictive power of the risk equalization model but also have shortcomings since they do not capture selection incentives (Van Kleef et al., 2024.; Layton et al., 2017; Layton et al., 2018; Van Kleef et al., 2018, Van de Ven and Van Kleef, 2025). However, these measures are informative when they are interpreted correctly. In this thesis, the R^2 and the CPM will be used to evaluate the explanatory power of the risk equalization model. These two measures provide complementary insights since the R^2 indicates the proportion of overall variance in healthcare spending explained by the model, while CPM indicates the absolute differences which reflect individual-level prediction accuracy. Since MAPE is similar to CPM, it will not be included in this thesis.

Since the R^2 , CPM, and MAPE do not capture selection incentives, group-level fit measures, such as the mean financial result, are used. The mean financial result is calculated for specific subgroups and shows the monetary difference between the predicted healthcare costs and the actual healthcare costs (Van Kleef et al., 2022.; Eijkenaar et al., 2019). Therefore, this measure indicates whether selection incentives are present. Research by Van Kleef et al (2013), showed that the mean undercompensation per person gradually decreased since the introduction of the risk equalization model in 1993 until 2009. However, subgroups with high healthcare costs were still undercompensated in 2009. Other, more recent studies have also showed that specific subgroups with high healthcare costs are still undercompensated, and that subgroups that have low healthcare costs are still overcompensated (Eijkenaar et al., 2019; Van Kleef et al., 2017; Withagen-Koster et al., 2022). A recent paper that evaluated the risk equalization model of 2024 and 2025 showed that for subgroups based on the presence or absence of a chronic condition, the risk equalization model fully compensates for the predictable high and low healthcare costs. However, certain subgroups with specific chronic conditions are still substantially under- or overcompensated (Van Kleef & Van Vliet., 2025). This financial result provides incentives for risk selection. It is particularly insightful to look at the mean financial result for subgroups that are sensitive to risk selection (Van Kleef et al., 2016).

3.7 Complexity and performance of the risk adjusters SES and SOI

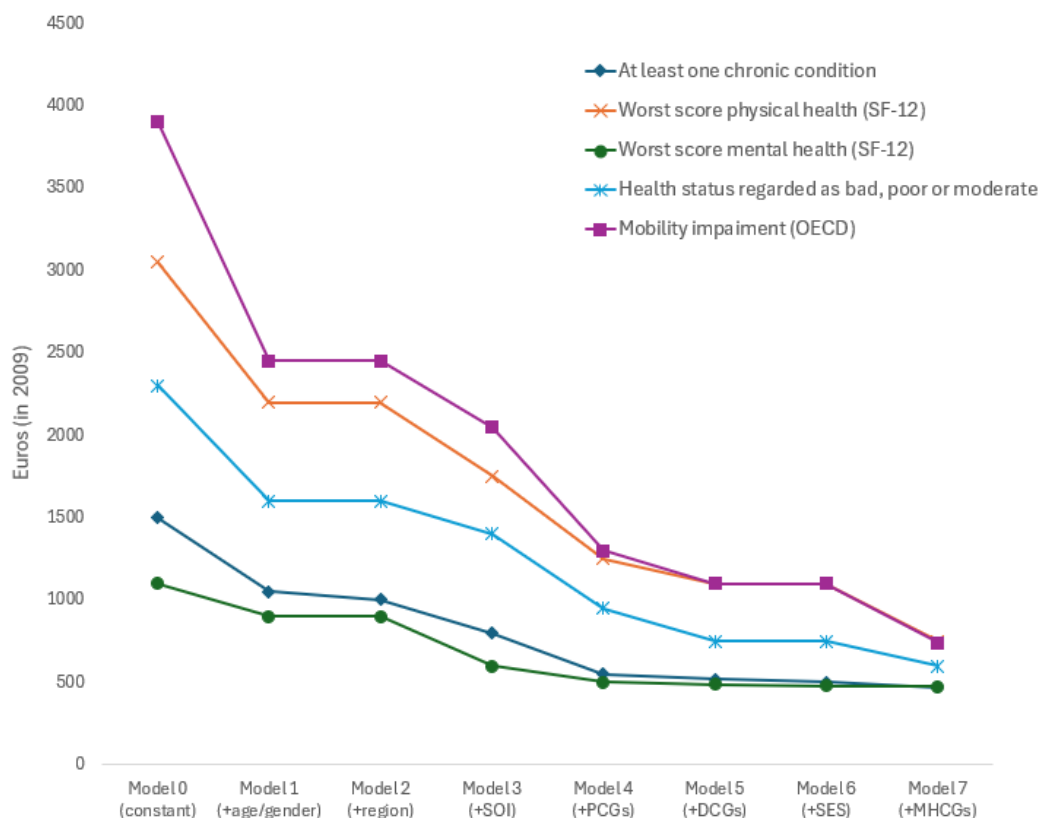
Hamstra et al. (2023) identified six aspects of risk adjusters that contribute to the complexity of the risk equalization model. These complex aspects are substantive coherence between risk adjusters, a large number of classes within a risk adjuster, instability of the model due to policy changes, complex individual steps needed in a risk adjuster, many steps needed for characteristic deviation, and reliance on multiple years of data. Based on these aspects, both SES and SOI can be classified as complex risk adjusters. SOI is complex across all six aspects, while SES is complex across five aspects since 'many steps needed for characteristic deviation' is not applicable.

First, substantive coherence between risk adjusters complicates the interpretation of year-to-year changes in risk classes and payment weights. For instance, DCG and SES are related, whereby a change in SES class can be caused by a change in income, but also by a change in the DCG class. This makes it difficult to isolate the effect of each variable. Second, SES consists of 12 risk classes and SOI consists of 36 risk classes. This large number of classes complicates the interpretation of the model and makes it more difficult to isolate the impact of specific model changes. Third, both risk adjusters are sensitive to policy changes, which can cause instability in classification and increases the complexity of the risk equalization model. For example, changes in registration procedures or income definitions may affect the classification of individuals under SES or SOI. Fourth, classifying individuals into the correct risk classes of

certain risk adjusters requires complex individual steps. SOI is a clear example of complex classification since classifying individuals into the correct SOI class depends on multiple administrative sources and specific rules about the sequence of classification. For SES, fewer individual steps are required, but the classification still requires multiple steps. Fifth, many steps are needed for characteristic derivation. This complex aspect only applies to SOI and not to SES. Lastly, both risk adjusters rely on multiple years of data, which increases the need for data validation and consistency over time. For SES, income data from various years and sources is used. For SOI, prior income and employment data may also influence classification (Hamstra et al., 2023).

Apart from the fact that SES and SOI are identified as complex risk adjusters, an earlier study by Van Kleef et al. (2013) showed that the contribution of SES and SOI is quite limited in the risk equalization model. Figure 1 in this thesis is based on Figure 1 of Van Kleef et al. (2013) and shows the extent of undercompensation (in 2009 euros) for various subgroups within the Dutch risk equalization model based on survey information. The x-axis shows multiple risk equalization models, where more risk adjusters are gradually added. The y-axis shows the level of undercompensation in euros. As more risk adjusters were added, the level of undercompensation declined for all subgroups. However, even in the most sophisticated model, all of the subgroups were still undercompensated.

Figure 1: Under compensation (in 2009 euros) in year t of subgroups based on survey information from year $t-1$ ^a



^a Note: This figure is based on figure 1 in Van Kleef et al. (2013)

When examining the added value of SES and SOI in more detail, Figure 1 shows that both risk adjusters have a modest contribution to the compensation for subgroups. Particularly, the introduction of SES (model 6) shows a limited impact, with minimal reductions in

undercompensation across all health status indicators. This risk adjuster was added after the inclusion of morbidity-based risk adjusters, which suggests that much of the compensation associated with SES may already be captured by previously added risk adjusters in the model. SOI (model 3) demonstrates a more substantial contribution in reducing the undercompensation. However, this added contribution occurs in a model that does not include morbidity-based risk adjusters. Therefore, this study will assess the added value of SES and SOI while considering all other risk adjusters in the risk equalization model. In addition, the potential contribution of including SES and SOI will be examined, which was not assessed in the study by Van Kleef et al. (2013). The study by Van Kleef et al. (2013) uses the risk equalization model of 2012, while this thesis will use the risk equalization model of 2025, which is more sophisticated.

4. Methods

The study design of this thesis was a quantitative simulation study using microdata, conducted with the statistical program STATA MP16. This chapter provides an overview of the general steps required to answer the research question. First, the dataset is described, followed by an explanation of the four steps needed for the data analysis. Lastly, the reliability and validity of this thesis are discussed.

4.1 Data

Two datasets containing microdata were used in this thesis. One dataset is from the Nivel Primary Care Database (NIVEL-PCD), which contains GP morbidity data from approximately 1,2 million registered patients (Vanhommerig et al., 2025; Nivel, 2022). The data are collected from electronic health record systems of around 400 general practices. This dataset contains 109 dummy variables that indicates whether a chronic condition was registered for an individual in 2021. Of these dummy variables, 103 are related to somatic care. This dataset allows to identify specific subgroups based on the presence of chronic conditions.

The supervisor of this thesis supplemented the Nivel-PCD with a risk equalization (RE) dataset that contains individual-level data on medical spending and information on all risk adjusters for 2022. This data came from various administrative sources and was used to estimate the payment weights for the risk equalization model of 2025. This dataset consists of approximately 1,6 million individuals covered by the Dutch health insurance act. By combining the Nivel-PCD with the RE-dataset, the predicted costs for each individual and specific subgroups could be determined. To ensure that the dataset was representative for the entire Dutch population, a weight factor was included in the analysis. This weight factor was developed in earlier work (Van Kleef & Van Vliet, 2025). Table 2 presents the descriptive statistics of the combined dataset used in this thesis. Non-residents were excluded from both the NIVEL-PCD and the RE-dataset, so therefore the risk adjuster 'non-residents' was not included in the analysis of this thesis.

Table 2: Descriptive statistics of healthcare spending and population characteristics ^{A, B}

Study population (n)	1,614,109
Weighted study population (n)	17,310,265
Mean healthcare costs in 2022	€ 2655.91
At least 1 DCG in 2022	11.64 %
At least 1 PCG in 2022	26.26 %
At least 1 chronic condition in 2021	59.3 %
Men (age)	
0-18	19.5 %
19-34	21.7 %
35-44	12.1 %
45-54	13.4 %
55-64	14.0 %
65+	19.3 %
Women (age)	
0-18	18.2 %
19-34	20.9 %
35-44	12.0 %
45-54	13.3 %
55-64	13.8 %
65+	21.7 %
SES class	
1 very low	21.7 %
2 low	19.6 %
3 middle	29.4 %
4 high	29.3 %
Source of income	
Completely unable to work	1.1 %
Partly unable to work	5.3 %
Social assistance beneficiaries	3.9 %
Students	4.0 %
Self-employed individuals	10.2 %
Highly educated individuals	7.1 %
Reference group	53.7 %
70+	14.6 %

^A Results are based on the 2021 Nivel-PCD and on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

4.2 Data analysis

The data analysis provided an answer to the second sub-question: To what extent do the risk adjusters 'socioeconomic status' and 'source of income' compensate for predictable spending variation between relevant subgroups:

- In a risk equalization model for somatic care without other risk adjusters?
- In the current risk equalization model for somatic care?

This question was addressed in four steps. First, different risk equalization models were simulated. Second, relevant subgroups were identified. Third, the mean financial result for these subgroups was calculated under the different models. Finally, the contribution of SES and SOI across the different models was compared.

4.2.1 Step 1: Simulation of the risk equalization model

To answer the research question, multiple risk equalization models were simulated, as shown in Table 3. The models were simulated using ordinary least-squares regression (OLS), with somatic healthcare spending in 2022 as the dependent variable and the risk adjusters of the risk equalization model of 2025 as independent variables. The risk adjusters were included as dummy variables. The focus of the analysis was on the predicted healthcare costs resulting from the different risk equalization models, rather than on the individual coefficients of the risk adjusters. OLS regression was used instead of constrained regression because applying constrained regression would have been too complex given the limited time available for this thesis.

Four different risk equalization models were simulated, and a brief description of each model is provided in Table 3. Model 0 excluded all risk adjusters, so for each individual the predicted costs equalled the mean healthcare costs in the population. A risk equalization model that only included SES and SOI (model 1) was then simulated to determine the potential contribution of these risk adjusters. The explicit interaction with age of these risk adjusters was excluded to isolate the potential contribution of SES and SOI. However, the risk adjuster SOI also contained an implicit interaction with age. To counteract this implicit interaction as much as possible, the risk class 70+ was added to the reference group. Thereafter, the actual risk equalization model (model 2) was replicated using the same data and steps used when estimating the actual risk equalization model. In addition, a model excluding SES and SOI, but including all other risk adjusters (model 3), was simulated to evaluate the impact of SES and SOI. This model was compared to the actual risk equalization model and showed the net contribution of SES and SOI in reducing predictable profits and losses (i.e., selection incentives).

Tabel 3: Overview of the simulated risk equalization models

Model	Description	Purpose
0	A model without any risk adjusters.	Shows the selection incentives in a hypothetical situation without risk equalization.
1	A model which only includes risk adjusters SES and SOI.	Determines the potential contribution of SES and SOI in reducing selection incentives.
2	The current risk equalization model, including all risk adjusters.	Shows the selection incentives under the actual risk equalization model.
3	The current risk equalization model without SES and SOI.	Compare to model 2 to show the net contribution of SES and SOI to the reduction of selection incentives.

To obtain an indication of the explanatory power, the four models were assessed using R^2 and Cumming's Prediction Measure (CPM), as defined in Formula 1 and Formula 2. In both formulas, Y_i indicates the observed healthcare costs of an individual, $\hat{Y}_i$ indicates the predicted healthcare costs of an individual, and $\bar{Y}$ reflects the mean observed costs of the population.

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

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

The R^2 indicated the proportion of variance in healthcare costs that is explained by the model, while the CPM reflected the extent to which the model explained the absolute differences in healthcare costs. Differences in R^2 and CPM across the four models provided insight into the contribution of SES and SOI to the explanatory power of the risk equalization model.

4.2.2 Step 2: Identification of relevant subgroups

Different subgroups were formed for which the mean financial result was calculated under different risk equalization models to indicate selection incentives related to these groups. These subgroups were based on individuals' health status as identified through the Nivel-PCD, and the clustering of indications followed the clustering described in Vanhommerig et al. (2025). Subgroups were formed based on the presence or absence of a chronic condition, as well as subgroups for specific chronic conditions such as diabetes, coronary heart disease, COPD, cancer and social disability. Additionally, subgroups based on SES and SOI were formed to examine the extent to which the mean financial result for these subgroups changed when the risk adjusters SES and SOI were excluded from the risk equalization model.

4.2.3 Step 3: Calculation of the mean financial result of relevant subgroups

To determine whether selection incentives were present, the mean financial result for each model and subgroup was calculated using the formula described in chapter 5 of McGuire and Van Kleeef (2018):

$$\text{Mean financial result}_g = \frac{\sum_{i \in g} (\hat{Y}_i - Y_i)}{n_g} \quad (3)$$

This formula was used to calculate the mean financial result for a subgroup g . In the formula, $\hat{Y}_i$ represents the predicted costs of individual i , while Y_i indicates the actual costs of i . The notation $i \in g$ refers to individuals belonging to subgroup g , and n_g indicates the number of individuals in that subgroup. A negative mean financial result indicated a predictable loss, while a positive result indicated a predictable profit. This calculation was applied to all models described in step 1 and to every subgroup.

4.2.4 Step 4: Comparison of the potential and net contribution of SES and SOI in reducing selection incentives

To answer sub-question 2a, the mean financial results of models 0 and 1 were compared and reflected the potential contribution of SES and SOI. Similarly, sub-question 2b was answered by comparing the mean financial results under model 2 and 3, which reflected the net contribution of SES and SOI. These comparisons helped determine the contribution of SES and SOI to risk equalization, particularly in terms of how SES and SOI affected selection incentives across subgroups. In addition, the net contribution as a percentage of potential contribution was calculated using Formula 4. This made it possible to assess the net contribution as a ratio of the potential contribution. A lower percentage indicated that a larger share of the variation was already captured by other risk adjusters in the risk equalization model.

$$\frac{\text{Net contribution of SES and SOI}}{\text{Potential contribution of SES and SOI}} \times 100\% \quad (4)$$

4.3 Validity & reliability

The RE-dataset used in this thesis, which contained individual-level data on medical spending, was also used to estimate the payment weights for the current risk equalization model of 2025. This strengthened this thesis, as the findings were representative of the actual risk equalization model. However, a limitation was that this thesis used a sample of approximately 1.6 million individuals included in the RE-dataset, rather than a dataset including all individuals covered by the Dutch health insurance act used in the actual model. In addition, this thesis used OLS regression instead of constrained regression, which could have affected the findings. Therefore, appendix 1 presents the mean financial result for subgroups under all models and the current risk equalization model of 2025 when constrained regression was used. Besides the RE-dataset, this thesis used the NIVEL-PCD. The subgroups formed in this thesis were based on the indication clustering as described in Vanhommerig et al. (2025). Since this type of clustering was followed, the results for these subgroups could be compared to other studies which used this NIVEL clustering.

The findings of this thesis provide valuable insights for other countries with a similar risk equalization model. However, when applying the findings of this thesis to another country, it is important to take into account the differences in the healthcare market and in the risk equalization model. Therefore, the exact numbers of the results aren't directly relevant for other countries. Nonetheless, the general patterns and conclusions may provide important insights for other countries and might help to make a well-informed choice regarding the inclusion of socioeconomic risk adjusters.

5. Results

As described in the method section, four steps were followed to answer the second sub-question: To what extent do the risk adjusters 'socioeconomic status' and 'source of income' compensate for predictable spending variation between relevant subgroups:

- In a risk equalization model for somatic care without other risk adjusters?
- In the current risk equalization model for somatic care?

First, the statistical performance in terms of explanatory power of the different risk equalization models is presented. Then, average healthcare costs of each subgroup are presented, which help to understand cost variation across groups. Thereafter, the contribution of SES and SOI to the reduction of selection incentives for subgroups based on a chronic condition is presented, followed by subgroups based on SES and SOI. Then, the potential and net contribution of SES and SOI to the mean financial result are compared.

5.1 Explanatory power

First, the statistical performance in terms of explanatory power of the different risk equalization models is presented. Table 4 presents the R^2 and CPM values for the different risk equalization models, which reflect the explanatory power. Examining the R^2 values, the model without any risk adjusters (model 0) explains no variation in healthcare spending, as expected ($R^2 = 0$). When only SES and SOI are included as risk adjusters (model 1), the model explains 1.16% of the variation in medical spending ($R^2 = 0.0116$). This represents the potential contribution of SES and SOI to the risk equalization model in terms of explanatory power. The current risk equalization model (model 2) has an R^2 of 0.3198, which means that it explains about 32% of the variation in healthcare spending. When SES and SOI are removed from this current risk equalization model (model 3), the R^2 decreases slightly to 0.3197. The net contribution of SES and SOI to the risk equalization model in terms of explanatory power is therefore 0.0001. So, while the potential contribution of SES and SOI to the risk equalization model is 0.0116, the net contribution is only 0.0001.

Table 4: Statistical performance of the different risk equalization models^A

Model	Description	R^2	(Cumming's prediction measure) CPM
0	A model without any risk adjusters	0	0
1	A model which only includes risk adjusters SES and SOI.	0.0116	0.0227
2	The current risk equalization model, including all risk adjusters.	0.3198	0.3542
3	The current risk equalization model without SES and SOI.	0.3197	0.3539

^A The R^2 is calculated using formula 1, and the CPM is calculated using formula 2.

In addition to the R^2 , Table 4 also presents the CPM values for the different risk equalization models. As expected, the model without any risk adjusters (model 0) shows no explanatory power, with a CPM value of 0. When only SES and SOI are included as risk adjusters in the risk equalization model (model 1), the CPM is 0.0227. This represents the potential contribution of

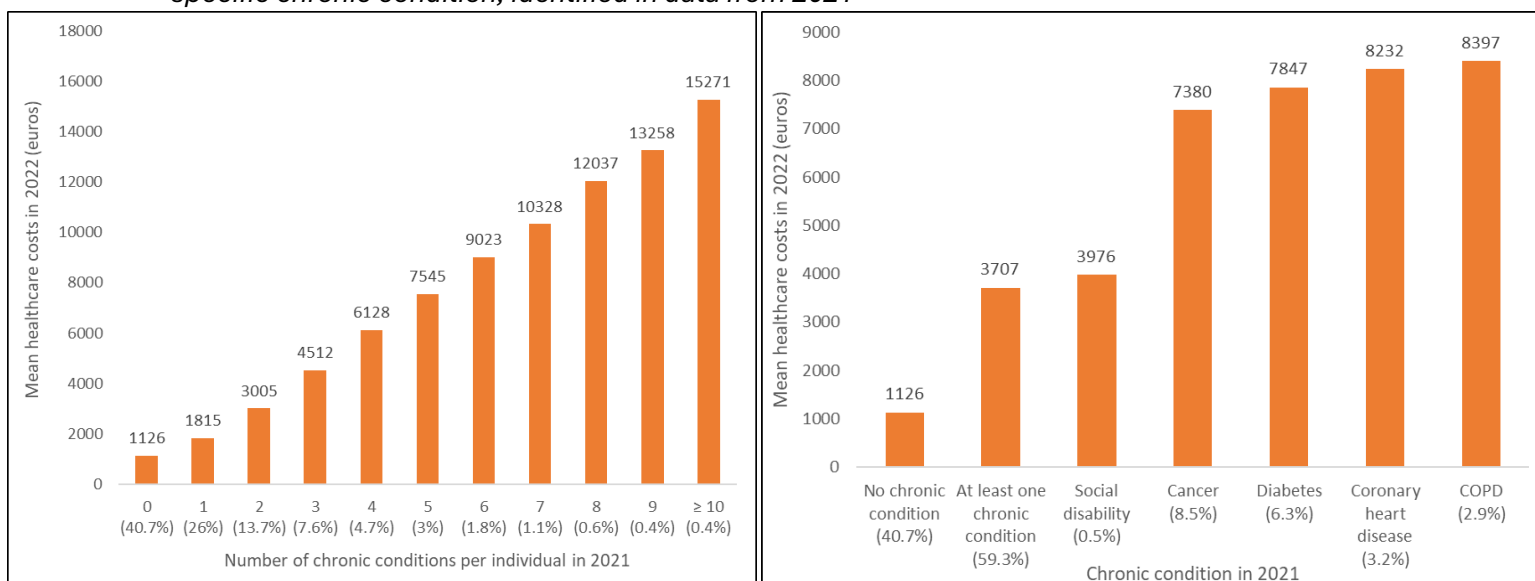
SES and SOI in terms of predictive accuracy. The current risk equalization model (model 2) has a CPM of 0.3542. When SES and SOI are removed from this current risk equalization model (model 3), the CPM decreases slightly to 0.3539. The net contribution of SES and SOI to the current risk equalization model in terms of predictive accuracy is therefore 0.0003. So, while SES and SOI have a potential contribution to the CPM of 0.0227, the net contribution to the CPM of the current risk equalization model is only 0.0003. Both the R^2 and CPM provide insight into the statistical performance of the risk equalization model. However, they do not reflect selection incentives.

5.2 Identification of subgroups

To illustrate cost differences within the population, several subgroups have been identified. These subgroups are based on the number of chronic conditions, specific chronic conditions, socioeconomic status, and source of income, as described in paragraph 4.2.2. For each subgroup, the average healthcare costs and prevalence within the population are presented.

Figure 1 presents the average healthcare costs in 2022 by number of chronic conditions per individual and by specific chronic condition, identified in data from 2021. The graph shows a clear upward trend when looking at the number of chronic conditions, indicating that average healthcare costs increase with each additional chronic condition. Individuals without chronic conditions (40.7 %) have average healthcare costs of € 1,126, whereas individuals with chronic conditions (59.3 %) have on average, more than three times higher healthcare costs (€ 3,707). The average healthcare costs increase with each additional chronic condition, rising to € 15,270 for individuals with ten or more chronic conditions. When examining specific chronic conditions, healthcare costs are highest for individuals with COPD (€ 8,397), followed by individuals with coronary heart disease (€ 8,232), diabetes (€ 7,847), cancer (€ 7,380), and social disability (€ 3,976).

Figure 1: Mean healthcare costs in 2022 by number of chronic conditions per individual and by specific chronic condition, identified in data from 2021 ^{A, B}

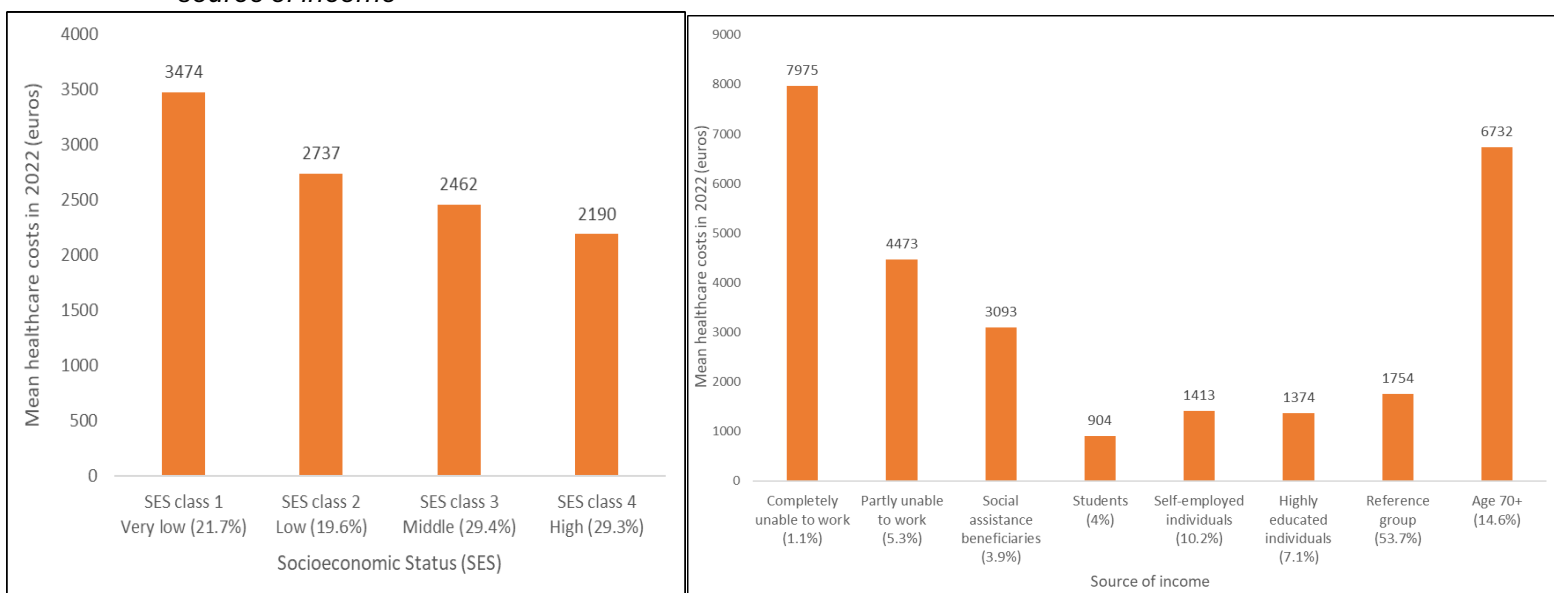


^A Results are based on the 2021 Nivel-PCD and on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

Healthcare costs vary across both socioeconomic groups and source of income. As shown in Figure 2, when assessing socioeconomic groups, individuals in the lowest SES class (SES class 1 very low) have the highest average healthcare costs (€ 3,474), while individuals in the highest SES class (SES class 4 high) have the lowest healthcare costs (€ 2,190). This represents a cost difference of almost € 1,300 between the highest and lowest SES groups. The cost difference becomes even more pronounced when examining source of income. Individuals who are completely unable to work have the highest average healthcare costs (€ 7,975), followed by individuals aged 70 and older (€ 6,732). In contrast, students have the lowest average healthcare costs (€ 904). This pattern indicates a relationship between source of income and healthcare costs, with cost differences of nearly €7,000 between the highest and lowest groups.

Figure 2: Mean healthcare costs in 2022 for subgroups based on socioeconomic status and source of income ^{A, B}



^A Results are based on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

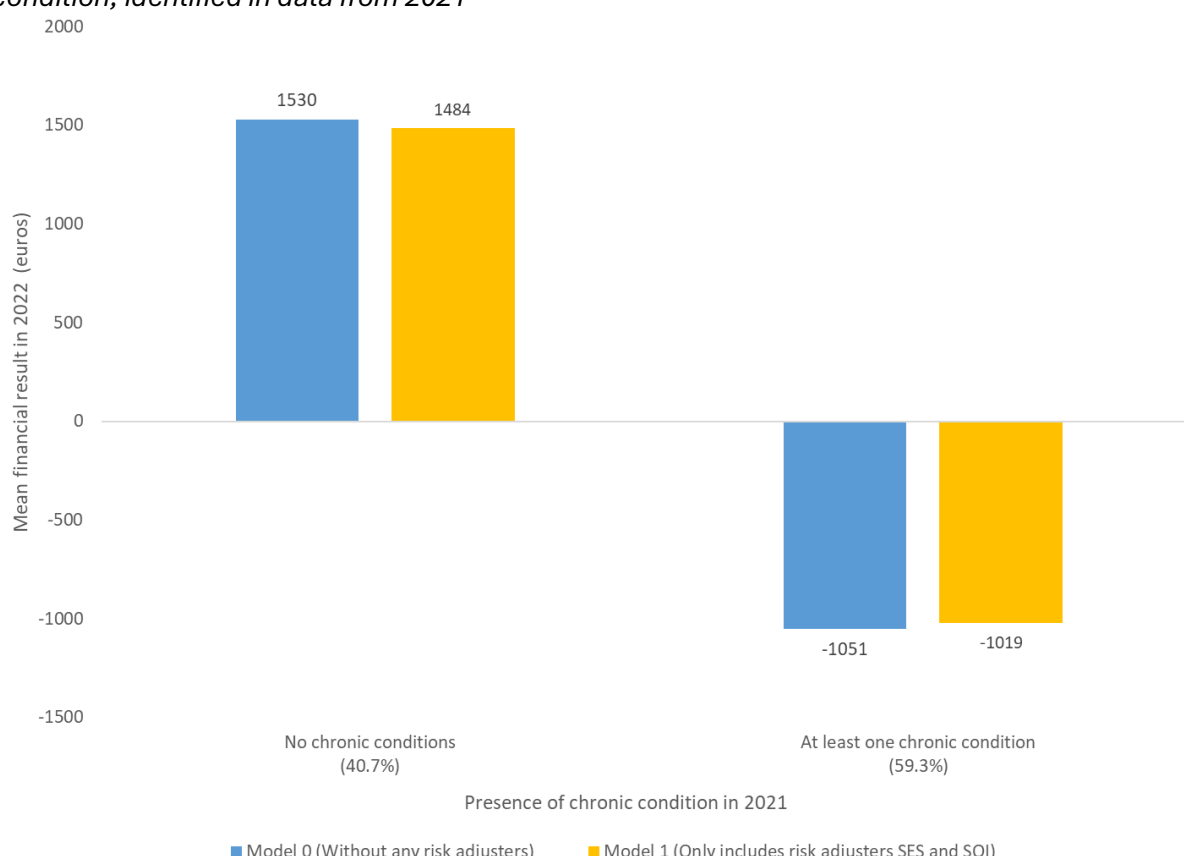
5.3 Contribution of SES and SOI to the reduction of selection incentives

This section presents the mean financial results for specific subgroups, where a positive value indicates predictable profits and a negative value indicates predictable losses. The mean financial result is calculated using Formula 3. These predictable profits and losses create selection incentives for insurers. First, subgroups based on the presence of chronic conditions will be presented, followed by subgroups based on specific chronic conditions. Then, subgroups based on socioeconomic status are presented, followed by subgroups based on source of income. The figures compare different risk equalization models to determine both the potential and net contribution of the risk adjusters SES and SOI. When models 0 and 1 are presented, the comparison shows the potential contribution of SES and SOI. This addresses the first part of the second sub-question: to what extent do the risk adjusters ‘socioeconomic status’ and ‘source of income’ compensate for predictable spending variation between relevant subgroups in a risk equalization model for somatic care without other risk adjusters? When models 2 and 3 are compared in figures, the net contribution of the risk adjusters SES and SOI is determined. This addresses the second part of the second sub-question: to what extent do the risk adjusters ‘socioeconomic status’ and ‘source of income’ compensate for predictable spending variation between relevant subgroups in the current risk equalization model for somatic care? Additionally, to provide a complete overview of how SES and SOI affect the financial result for subgroups, appendix 2 presents the total financial result for all subgroups under model 2 and model 3.

5.3.1 Subgroups based on the presence of a chronic condition

Figure 3 presents the mean financial results in 2022 for individuals based on the presence or absence of chronic conditions under model 0 (without any risk adjusters) and model 1 (only includes risk adjusters SES and SOI). In both models, individuals without a chronic condition are overcompensated (mean financial result = € 1,530 and € 1,484) and individuals with a chronic condition are undercompensated (mean financial result = € -1,051 and € -1,019). The potential contribution of SES and SOI is therefore € 46 for individuals without a chronic condition and € 32 for individuals with a chronic condition.

Figure 3: Mean financial result in 2022 under model 0 (without any risk adjusters) and model 1 (only includes risk adjusters SES and SOI) for individuals based on the presence or absence of a condition, identified in data from 2021 ^{A, B, C}



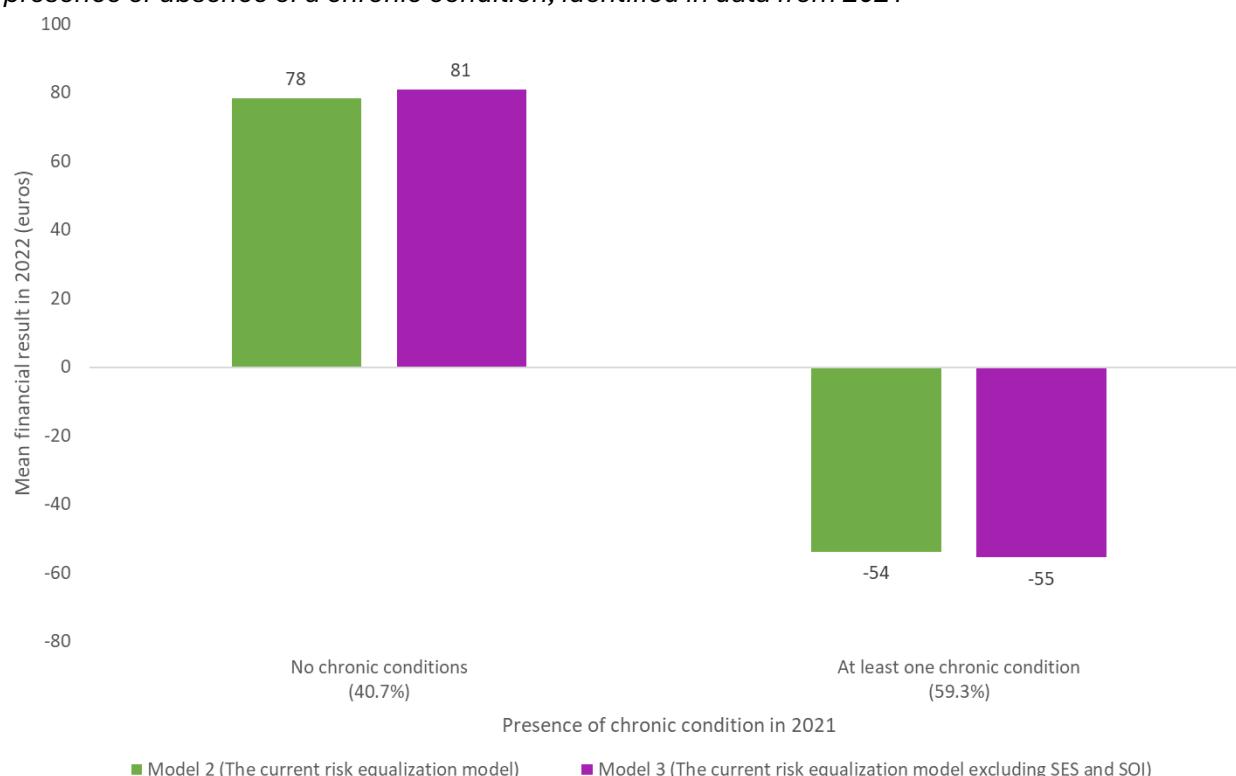
^A Results are based on the 2021 Nivel-PCD and on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income

Figure 4 presents the mean financial result in 2022 for individuals based on the presence or absence of chronic conditions under model 2 (the current risk equalization model) and model 3 (the current risk equalization model excluding SES and SOI). In both models, individuals without a chronic condition are overcompensated (mean financial result = € 78 and € 81) and individuals with a chronic condition are undercompensated (mean financial result = € -54 and € -55). The net contribution of SES and SOI is therefore € 3 for individuals without a chronic condition and € 1 for individuals with a chronic condition.

Figure 4: Mean financial result in 2022 under model 2 (the current risk equalization model) and model 3 (the current risk equalization model excluding SES and SOI) for individuals based on the presence or absence of a chronic condition, identified in data from 2021 ^{A, B, C}



^A Results are based on the 2021 Nivel-PCD and on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

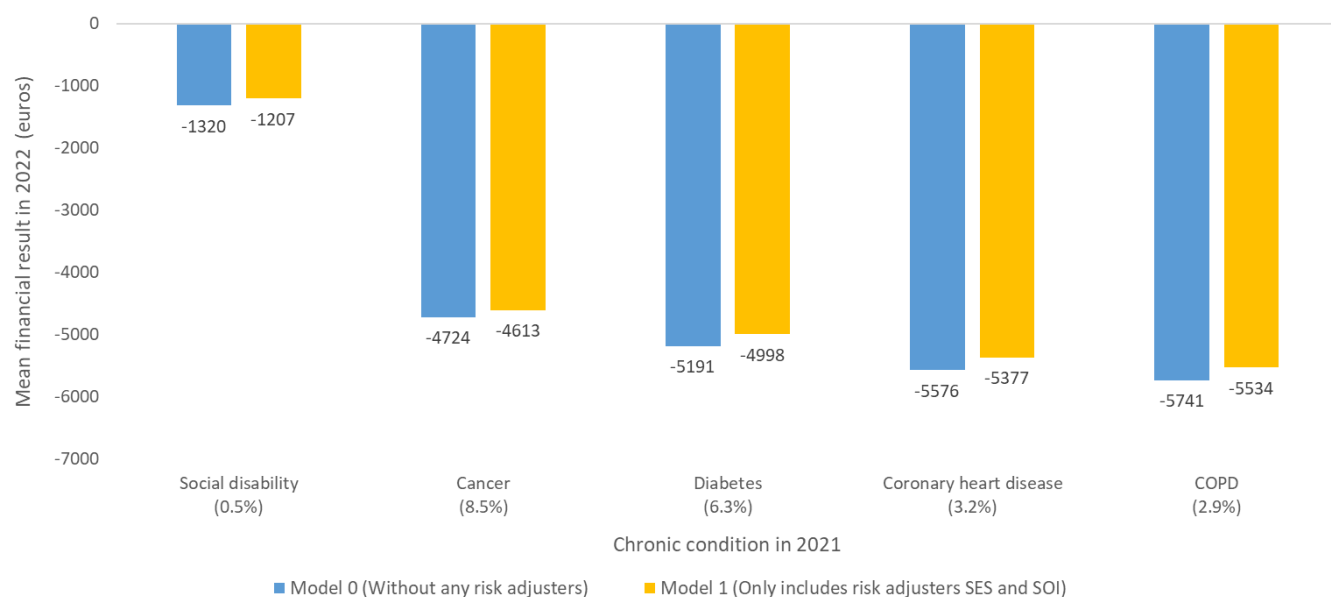
^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income

5.3.2 Subgroups based on specific chronic conditions

Figure 5 presents the mean financial result for subgroups based on chronic conditions under model 0 (without any risk adjusters) and model 1 (only includes risk adjusters SES and SOI). Under model 0, all chronic condition subgroups are undercompensated, with mean financial result ranging from € - 1,320 for individuals with a social disability to € - 5,741 for individuals with COPD. When only the risk adjusters SES and SOI are included (model 1), the mean financial result improves for all subgroups, ranging from a mean financial result of € - 1,207 for individuals with a social disability to € - 5,534 for individuals with COPD. All chronic condition subgroups remain undercompensated in both models, indicating predictable losses for insurers.

Figure 5: Mean financial result in 2022 under model 0 (without any risk adjusters) and model 1 (only includes risk adjusters SES and SOI) by chronic conditions, identified in data from 2021 ^{A,B, C}



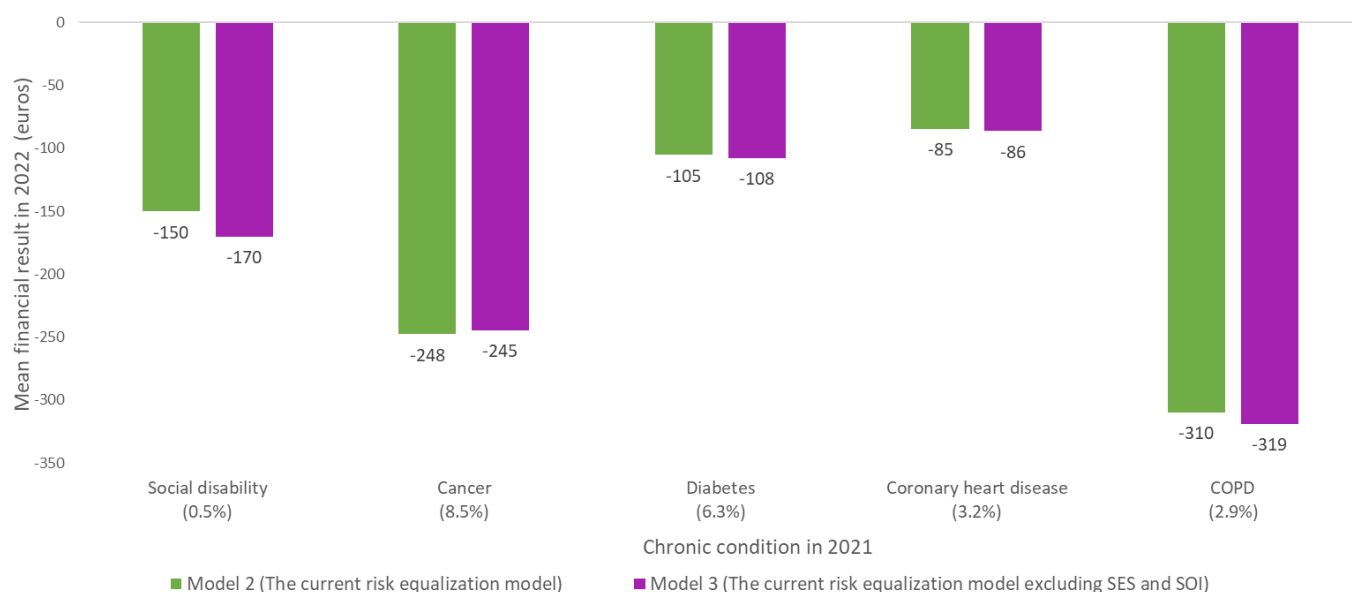
^A Results are based on the 2021 Nivel-PCD and on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income

Figure 6 presents the mean financial result for subgroups based on chronic conditions under model 2 (the current risk equalization model) and model 3 (the current risk equalization model excluding SES and SOI). In both models, all chronic condition subgroups remain undercompensated. In the current risk equalization model (model 2), the mean financial result ranges from € -85 for individuals with coronary heart disease to € -310 for individuals with COPD. Excluding the risk adjusters SES and SOI (model 3) results in a modest increase in the mean financial result for most subgroups. For individuals with coronary heart disease, the under compensation increases slightly from € -85 to € -86. For individuals with COPD, the mean financial result increases from € -310 to € -319, and for individuals with a social disability, the mean financial result increases from € -150 to € -170. For one subgroup, individuals with cancer, model 3 leads to a reduction of the mean financial result compared to model 2 (mean financial result = € -248 vs € -245). These findings suggest that excluding the risk adjusters SES and SOI from the risk equalization model leads to modestly higher predictable losses for insurers across most chronic condition subgroups. However, for the cancer subgroup, insurers face slightly lower predictable losses when SES and SOI are excluded from the risk equalization model.

Figure 6: Mean financial result in 2022 under model 2 (current risk equalization model) and model 3 (current risk equalization model excluding SES and SOI) by chronic conditions, identified in data from 2021 ^{A, B, C}



^A Results are based on the 2021 Nivel-PCD and on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

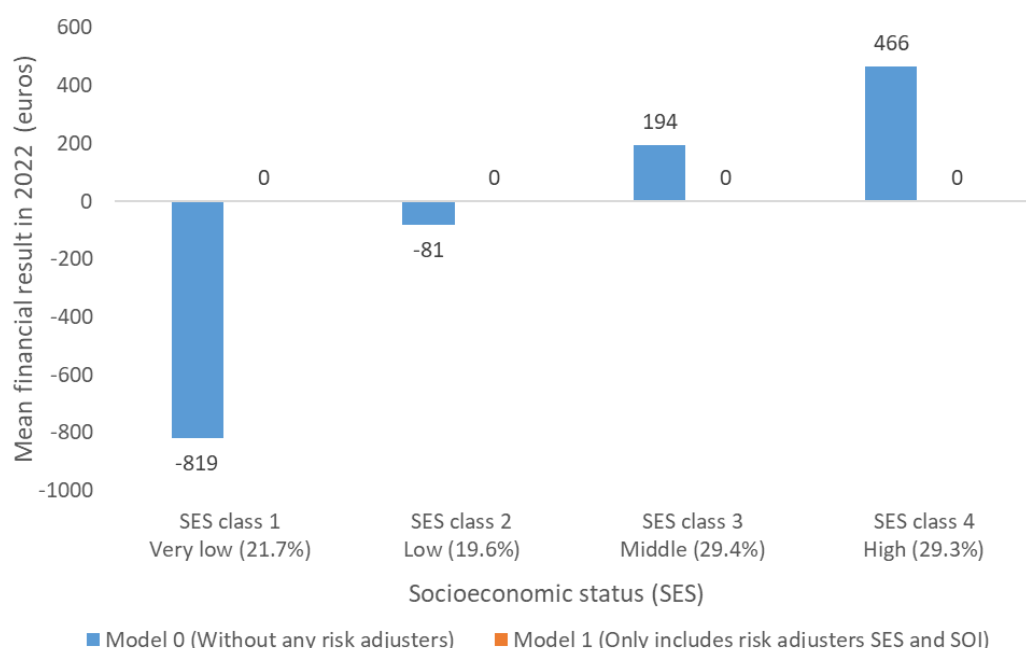
^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income

5.3.3 Subgroups based on socioeconomic status

The mean financial result for subgroups based on SES class under model 0 (without any risk adjusters) and model 1 (only includes risk adjusters SES and SOI) is illustrated in Figure 7. Without any risk equalization, insurers face predictable losses for individuals in lower SES classes, while individuals in a higher SES class are predictably profitable. Under model 0, the mean financial result ranges from € - 819 for individuals in the lowest SES class (SES class 1 very low), to € 466 for individuals in the highest SES class (SES class 4 high). Including SES and SOI as risk adjusters in the risk equalization model results in a mean financial result of € 0 for all SES classes.

Figure 7: Mean financial result in 2022 under model 0 (without any risk adjusters) and model 1 (only includes risk adjusters SES and SOI) by socioeconomic status ^{A,B, C}



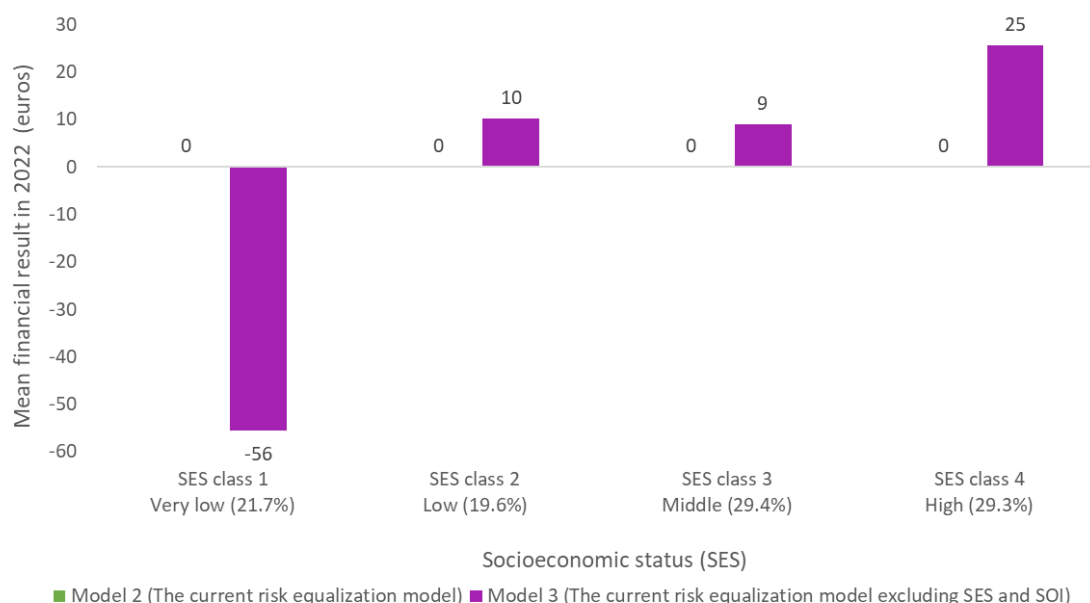
^A Results are based on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income

Figure 8 presents the mean financial result for subgroups based on SES class under model 2 (the current risk equalization model) and model 3 (the current risk equalization model excluding SES and SOI). Under model 2, the mean financial result for all SES classes is € 0. However, when SES and SOI are excluded from the current risk equalization model (model 3), the lowest SES class (SES class 1 very low) has a mean financial result of € - 56. This indicates that insurers face predictable losses for individuals in this subgroup. In contrast, the remaining SES classes have a positive mean financial result, which indicates that these subgroups are predictably profitable for insurers. These predictable profits and losses create selection incentives for insurer against these groups. The highest SES class (SES class 4 high) has the highest mean financial result of € 25. In addition, Figure 2 showed that individuals in the lower SES classes have higher average healthcare costs compared to the subgroups with positive mean financial results in Figure 8.

Figure 8: Mean financial result in 2022 under model 2 (current risk equalization model) and model 3 (current risk equalization model excluding SES and SOI) by socioeconomic status ^{A,B,C}



^A Results are based on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

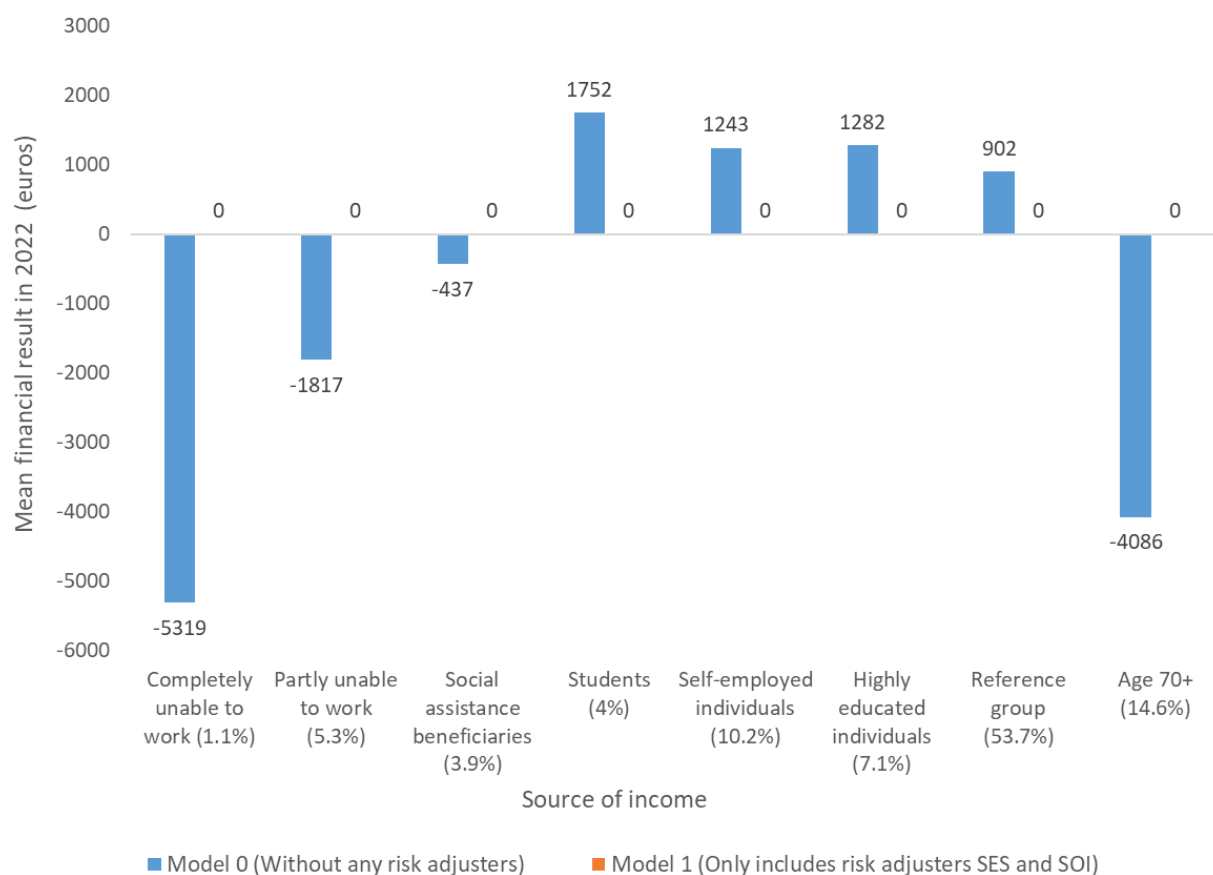
^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income

5.3.4 Subgroups based on source of income

The mean financial result for subgroups based on source of income under model 0 (without any risk adjusters) and model 1 (only includes risk adjusters SES and SOI) is illustrated in Figure 9. Without any risk equalization, insurers face predictable losses for individuals who are completely unable to work (mean financial result = € -5319), partly unable to work (mean financial result = € -1817), receive social assistance beneficiaries (mean financial result = € -437), and individuals aged 70 and older (mean financial result = € -4086). In contrast, the remaining groups are predictably profitable with mean financial results ranging from € 902 for the reference group to € 1752 for students. Including SES and SOI as risk adjusters in the risk equalization model results in a mean financial result of € 0 for all SOI classes.

Figure 9: Mean financial result in 2022 under model 0 (without any risk adjusters) and model 1 (only includes risk adjusters SES and SOI) by source of income ^{A,B,C}



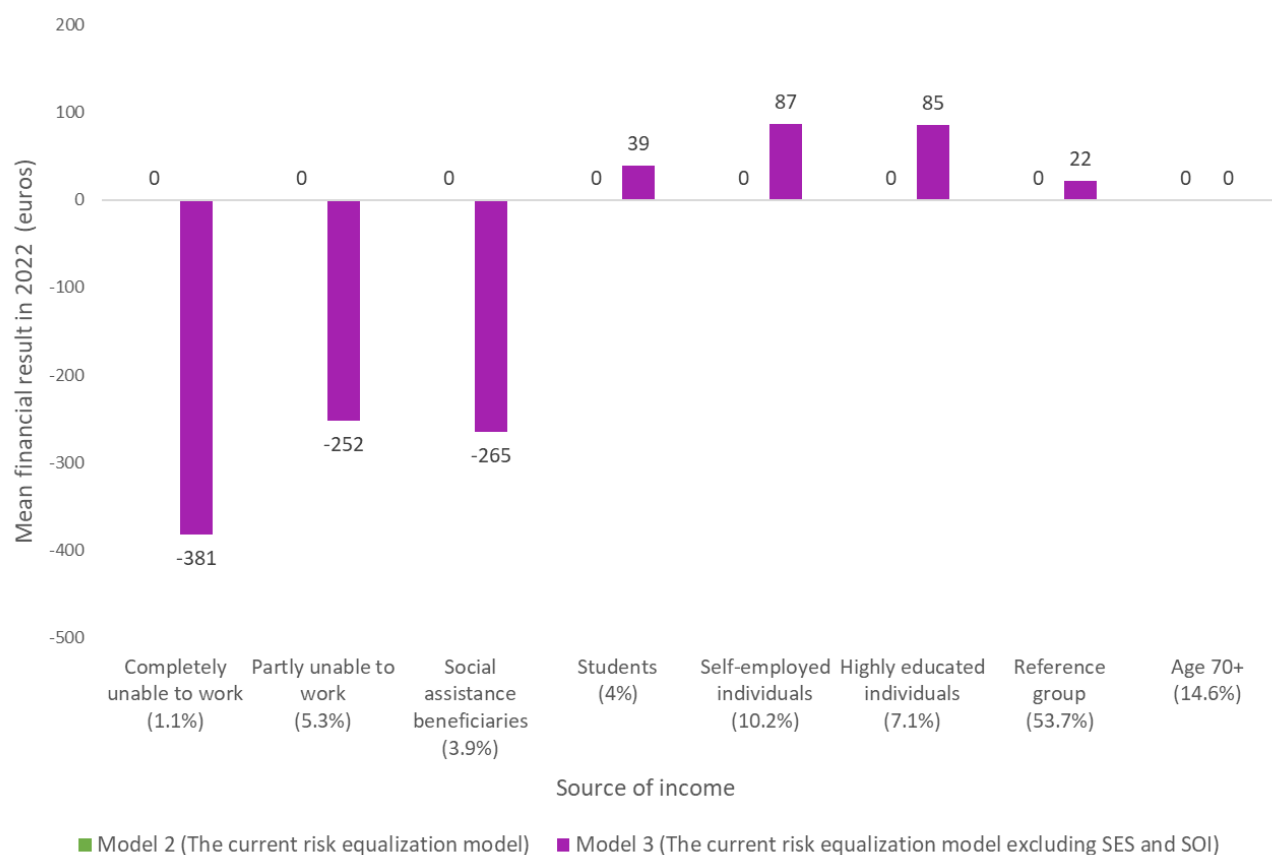
^A Results are based on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income

Figure 10 presents the mean financial results for subgroups based on source of income under model 2 (the current risk equalization model) and model 3 (the current risk equalization model excluding SES and SOI). Under model 2, the mean financial result for all source of income subgroups is € 0. Additionally, the mean financial result for individuals aged 70 or above is € 0, as this group is completely compensated through the age risk adjuster. When SES and SOI are excluded from the current risk equalization model (model 3), insurers face predictable losses for individuals in lower source of income subgroups. The mean financial result is € -381 for individuals who are completely unable to work, € -252 for individuals who are partly unable to work, and € -265 for individuals receiving social assistance beneficiaries. In contrast, the remaining subgroups are predictably profitable for insurers, with mean financial results ranging from € 22 for the reference group to € 87 for self-employed individuals. In addition, Figure 2 showed that individuals who are completely unable to work, partly unable to work or who receive social assistance beneficiaries, have higher average healthcare costs compared to the subgroups with positive mean financial results in Figure 10. This creates incentives for risk selection.

Figure 10: Mean financial result in 2022 under model 2 (current risk equalization model) and model 3 (current risk equalization model excluding SES and SOI) by source of income ^{A,B,C}



^A Results are based on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income

5.4 Comparison of the potential and net contribution of SES and SOI

In the previous paragraph, the mean financial results across subgroups under different risk equalization models were presented. The differences between the mean financial results under model 0 and model 1 represent the potential contribution of the risk adjusters SES and SOI. Table 5 presents this potential contribution in terms of mean financial result, which is derived from Figures 3, 5, 7 and 9. Similarly, the net contribution is derived from the differences between the mean financial results under model 2 and 3. Figures 4, 6, 8 and 10 show the net contribution of SES and SOI for different subgroups. The net contribution is also shown in Table 5. When comparing the potential and net contributions, a positive value indicates a reduction in the mean financial result when SES and SOI are included in a risk equalization model, which implies reduced selection incentives. Additionally, Table 5 includes the net contribution as a percentage the potential contribution, which indicates the proportion of the potential contribution that is achieved by including SES and SOI.

Table 5: Reduction in absolute mean financial results (in euros) and realized potential contribution (in percentage) of the risk adjusters SES and SOI, by subgroup ^{A, B, C, D}

Subgroup	Potential contribution of the risk adjusters SES and SOI (€)	Net contribution of the risk adjusters SES and SOI (€)	Net contribution as a percentage of potential contribution
At least one chronic condition			
Yes	143	2	1.2 %
No	208	3	1.2 %
Diabetes	478	2	0.5 %
COPD	553	9	1.7 %
Cancer	297	-3	-1.0 %
Social disability	231	20	8.7 %
Coronary heart disease	436	2	0.4 %
SES class:			
1 very low	819	56	6.8 %
2 low	81	10	12.6 %
3 middle	194	9	4.6 %
4 high	466	25	5.5 %
Source of income:			
Completely unable to work	5319	381	7.2 %
Partly unable to work	1817	252	13.9 %
Social assistance beneficiaries	437	265	60.5 %
Students	1752	39	2.2 %
Self-employed individuals	1243	87	7.0 %
Highly educated individuals	1282	85	6.6 %
Reference group	902	22	2.4 %
70+	4086	0	0 %

^A A positive value indicates a reduction of the mean financial result (euros) when SES and SOI are included in a risk equalization model.

^B The potential contribution is derived from the difference in mean financial result between model 0 and 1. The net contribution is derived from the difference in mean financial result between model 3 and 2.

^C Results are based on the 2021 Nivel-PCD and on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^D SES is Socioeconomic Status; SOI is Source of Income

The net contribution of SES and SOI to the mean financial result is positive for most subgroups, which indicates that SES and SOI contribute to reducing the mean financial results. This reduction means less predictable profits and losses, thereby decreasing selection incentives for insurers when SES and SOI are included as risk adjusters. For the subgroup cancer, including SES and SOI as risk adjusters slightly leads to increased selection incentives. Overall, the proportion of the potential contribution that is actually realized is limited. Across all subgroups, social assistance beneficiaries achieve the highest realization, since 60.5% of the potential contribution is realized in the net contribution.

6. Conclusion and discussion

In this thesis, the contribution of the risk adjusters SES and SOI to the performance of the Dutch risk equalization model for somatic care was examined. Over time, the Dutch risk equalization model has evolved into a sophisticated model where more morbidity-based risk adjusters were added gradually. This improved the performance but also increased the complexity of the risk equalization model. While removing SES and SOI as risk adjusters could decrease the complexity, the effect on the performance of the risk equalization model remained unclear.

6.1 Summary of findings

The risk adjusters SES and SOI were added to the Dutch risk equalization model in 2008 and 1995, respectively. Since individuals classified in a lower SES class or with a lower source of income generally have higher healthcare costs, the inclusion of these risk adjusters was intended to better predict individual healthcare costs and create an equal playing field for insurers. By compensating insurers more adequately for the higher healthcare costs of these high-risk subgroups, SES and SOI helped to reduce incentives for risk selection against these vulnerable individuals. Therefore, SES and SOI contribute to fairness in the healthcare system. However, Hamstra et al. (2023) identified SES and SOI as complex risk adjusters based on several criteria. For example, the large number of risk classes (12 risk classes for SES and 36 risk classes for SOI), complicates the interpretation of the model and makes it more difficult to isolate the impact of specific model changes. Removing the risk adjusters SES and SOI would decrease the complexity of the risk equalization model.

The extent to which SES and SOI compensate for predictable spending variation between subgroups was examined by analysing the potential and net contribution of these risk adjusters. The potential contribution is measured by comparing a risk equalization model without any other risk adjusters (model 0) to a risk equalization model that only includes the risk adjusters SES and SOI (model 1). The potential contribution to the statistical performance in terms of explanatory power is $R^2 = 0.0116$. The net contribution is assessed by comparing the current risk equalization model (model 2) to the current risk equalization model excluding SES and SOI (model 3). The net contribution of SES and SOI to the R^2 is 0.0001. The difference between the potential and net contribution indicates that the contribution of SES and SOI in terms of explanatory power is limited. This suggests that other risk adjusters in the risk equalization model capture most of the variation that these risk adjusters can explain. The Cummings Prediction Measure (CPM) shows a similar pattern, with a potential contribution of 0.0227 and a net contribution of 0.003, but has higher absolute values compared to R^2 . The CPM values are higher because this measure is more sensitive to prediction errors for individuals with higher healthcare costs. This suggests that SES and SOI may retain some value in predicting high healthcare costs. However, most of this effect is already captured by other risk adjusters in the model. Therefore, the added value of SES and SOI to the statistical performance in terms of explanatory power is limited.

Although R^2 and CPM provide insight into the statistical performance of the risk equalization model, they do not capture selection incentives that insurers face. Therefore, this thesis also evaluated the potential and net contribution of the risk adjusters SES and SOI by analysing the mean financial result, which reflects predictable profits and losses. These predictable profits and losses create selection incentives for insurers. As illustrated in Figure 6, for most chronic diseases, excluding the risk adjusters SES and SOI from the current risk equalization model increases the mean financial result and therefore increases the selection incentives. An exception is the subgroup cancer, where the mean financial result decreases when SES and SOI are excluded, indicating reduced selection incentives. Overall, while excluding SES and SOI as

risk adjusters from the current risk equalization model would increase selection incentives for subgroups based on chronic conditions, the extent is limited. In addition, the proportion of the potential contribution that is actually realized is limited as well, which is presented in Table 5. This implies that most of the potential contribution that SES and SOI can explain, is already captured by other risk adjusters in the current model.

When examining vulnerable subgroups based on SES and SOI, the impact of excluding these risk adjusters from the current risk equalization model is more substantial. This is also shown in appendix 2, which presents the total financial result for all subgroups. Specifically, for the SOI classes completely unable to work, partly unable to work, and social assistance beneficiaries, insurers face predictable losses. On the other hand, the remaining subgroups based on source of income are predictably profitable for insurers. A similar pattern is observed when evaluating the different SES classes. Insurers face predictable losses for individuals classified in SES class 1 (very low) and predictable profits for the remaining SES classes when the risk adjusters SES and SOI are excluded from the risk equalization model. When comparing the potential and net contribution of SES and SOI, the proportion of the potential contribution that is actually realized is limited, as presented in Table 5. This implies that selection incentives related to SES and SOI, which would arise in the absence of risk equalization, are already largely captured by other risk adjusters in the current model. An exception is the social assistance beneficiaries subgroup, where 60.5% of the potential contribution is achieved.

This thesis contributes to the existing literature on the Dutch risk equalization model for somatic care by presenting both the potential and net contribution of the risk adjusters SES and SOI. Previous studies, which have primarily focused on the net contribution, provide a more limited perspective of these risk adjusters. By explicitly comparing both the potential and net contribution, this thesis provides a more comprehensive understanding of the role of the risk adjusters SES and SOI. In addition, this thesis analyses selection incentives for specific, vulnerable subgroups, which adds value in evaluating the risk equalization model in terms of selection incentives.

6.2 Strengths, limitations and directions for future research

This thesis used two comprehensive datasets to analyse the Dutch risk equalization model for somatic care. The NIVEL-PCD dataset allowed identification of specific subgroups based on chronic conditions in 2021. This dataset was supplemented with individual-level data on medical spending and information on all risk adjusters for 2022, which was also used in estimating the payment weights for the current risk equalization model of 2025. By combining these datasets, this thesis used the most recent and comprehensive data available for analysing the Dutch risk equalization model, which enhances the relevance of the findings. Despite the comprehensive dataset, there are also limitations with the data used. The data available for this thesis included approximately 1,6 million individuals, instead of data covering the full population insured under the Dutch health insurance act. To correct for this, a weight factor developed by Van Kleef & Van Vliet. (2025) was used to make the dataset representative of the full population insured under the Dutch health insurance act. However, this weight factor is based on the total subpopulation, and not necessarily within specific subgroups. Since the weight factor may not fully correct for differences within specific subgroups, specific subgroups may still be under- or overrepresented. Future research could address this by replicating the analysis using data covering the full population insured under the Dutch health insurance act.

While constrained regression is used to estimate the payment weights for the current risk equalization model of 2025, this thesis applies OLS regression. OLS regression is used because

applying constrained regression would be too complex given the limited time available for this thesis. Constrained regression imposes specific restrictions on the estimated payment weights. It is likely that this different type of regression would have led to different absolute numbers. Appendix 1 presents the mean financial results for subgroups based on the SES and SOI classes, including the mean financial result under the current risk equalization model using constrained regression. In the current risk equalization model simulated with OLS regression (model 2), there are no financial imbalances across the different SES and SOI classes. According to the current risk equalization model using constrained regression, the lower SES and SOI classes have a positive mean financial result, while the higher SES and SOI classes have a negative mean financial result. This illustrates that the use of constrained regression influences the financial results across subgroups. This thesis could not assess the impact of excluding SES and SOI as risk adjusters (model 3) using constrained regression. Future research could extend this analysis by applying constrained regression to all models, and particularly to model 3.

Additionally, the actual extent of selection incentives depends not only on whether insurers face predictable profits and losses for specific subgroups, but also on how insurers respond to these changed incentives. When certain subgroups, such as individuals who are completely unable to work, are structurally over- or undercompensated, multiple actions by insurers as a reaction to these selection incentives are possible, as described in section 3.2 of this thesis. However, the degree to which the predictable profits and losses lead to risk selection in practice depends on the extent of insurer responsiveness to those selection incentives. Therefore, a direction for future research would be to examine the extent to which insurers respond to changes in selection incentives. For example, insurer behaviour, such as marketing strategies, could be analysed over time to assess how insurers react to adjustments of the risk equalization model. A better understanding of this responsiveness would provide insight into the impact of changed selection incentives and can help to develop more effective policy interventions.

Besides the risk adjusters SES and SOI, Hamstra et al. (2023) identified other risk adjusters that contribute to the complexity of the risk equalization model. For other complex socioeconomic risk adjusters, such as region, a similar analysis to what is done in this thesis for SES and SOI can be applied in future studies. Morbidity-based risk adjusters, such as DCG and PCG, also consist of complex elements. Future research could evaluate how the complexity of these risk adjusters can be decreased, while the impact on the performance of the risk equalization model is minimized.

Lastly, since this thesis focuses on the performance of the risk adjusters SES and SOI within the risk equalization model for somatic care, the findings are not directly applicable to the risk equalization model for mental care. Therefore, a direction for future research would be to replicate the analysis of this thesis for the risk equalization model for mental care. This would provide a broader understanding of the performance of SES and SOI and will contribute to improving the risk equalization model in the Netherlands.

6.3 Policy implications

The findings of this thesis suggest that policymakers may consider re-evaluating the inclusion of the risk adjusters SES and SOI in the risk equalization model for somatic care. Although the net contribution of SES and SOI to reducing predictable variation in mean financial results is limited, these risk adjusters still play a role in counteracting selection incentives, particularly for vulnerable subgroups such as individuals in SES class 1 (very low), those who are completely unable to work, partly unable to work, and social assistance beneficiaries. Policymakers could weight this added value against the complexity that these risk adjusters add to the model.

Furthermore, when examining the absolute differences in mean financial results presented in appendix 1, the differences in mean financial results between the current risk equalization model using constrained regression and the current risk equalization model excluding SES and SOI (model 3) are limited. Given that the mean financial results in the current risk equalization model using constrained regression are considered to be acceptable from a policy perspective, this suggests that the mean financial results from the risk equalization model excluding SES and SOI (model 3) may also fall within acceptable policy standards.

The decision to include or exclude these risk adjusters also depends on the goal of the risk equalization model. If the goal is to minimize selection incentives across all subgroups, policymakers might consider including the risk adjusters SES and SOI. However, when the policy focus shifts toward simplifying the model, removing SES and SOI as risk adjusters could be considered. In addition, when policymakers consider changes in the risk equalization model in general, it might be good to assess the impact these changes have on the complexity of the model. By doing so, increases in complexity may be prevented.

Additionally, policymakers could consider making decisions at the level of individual risk classes within a risk adjuster, since there are considerable differences in the contribution within a risk adjuster. Specifically for the risk adjuster SOI, the analysis in this thesis indicates that the risk classes completely unable to work, partly unable to work, and social assistance beneficiaries, contribute substantially to reducing selection incentives. Removing this entire risk adjuster would lead to increased selection incentives for these vulnerable groups. If policymakers consider retaining the risk classes completely unable to work, partly unable to work, and social assistance beneficiaries, and to exclude the other risk classes within SOI, the complexity of the risk equalization model would decrease. By retaining some risk classes, the effect of increased selection incentives for these vulnerable groups will be limited. The same might be considered for the risk class SES class 1 (very low). Within the risk adjuster SES, excluding the entire risk adjusters leads to the largest increase in selection incentives for this risk class. However, this effect is modest compared to the differences between risk classes within the risk adjuster SOI.

When policymakers consider excluding the risk adjusters SES and SOI from the risk equalization model, multiple insurer actions are possible as a response to increased selection incentives. Section 3.2 of this thesis described multiple insurer actions in response to selection incentives. Some of these may affect the vulnerable SES and SOI subgroups if these risk adjusters are excluded from the risk equalization model. First, insurers can make their insurance plan less attractive for individuals with a low SES or SOI through cost-sharing mechanisms, as these individuals are more sensitive to out-of-pocket expenses. For example, an insurer could offer an insurance plan with a limited provider network and high co-payments for out-of-network care. This would deter individuals with a low SES or SOI from choosing this plan. At the same time, plans with a broader provider network and lower co-payments will be more expensive. As a result, individuals with low incomes, who often have higher healthcare needs, are more likely to choose a more expensive plan. This threatens the solidarity of the healthcare system. In addition, insurers can design their marketing strategy in such a way that it targets individuals with a higher SES or SOI. For example, an insurer could promote their insurance plan by advertising with a fitness app, which is more attractive to a younger and healthier population. Moreover, insurers can take advantage of the fact that individuals with a lower SES or SOI may have difficulties in understanding the complex healthcare system. As a result, insurers might lower the quality of customer service by, for example, decreasing the accessibility, which could deter these individuals from enrolling in a particular health insurance. Lastly, most individuals take both their basic and supplementary health insurance from the same insurer. Insurers could increase premiums for supplementary insurance plans or make the information about these supplementary insurance plans unclear and difficult to compare. This might discourage

unprofitable subgroups from enrolling. Another possible effect of increased selection incentives against individuals with low SES or SOI is the impact on municipal health insurance policies. Through these policies, insurers and municipalities collaborate to offer more affordable health insurance plans to vulnerable individuals. However, increased selection incentives against these vulnerable subgroups may reduce insurers' willingness to participate in such municipal health insurance programs, thereby undermining the effectiveness of these policies. All these insurer actions are possible if policymakers choose to exclude the risk adjusters SES and SOI from the risk equalization model. This would increase the risk selection against vulnerable groups and undermine the fairness of the Dutch healthcare system. However, the question remains whether these increased selection incentives are strong enough for insurers to engage in risk selection.

Other countries with similar risk equalization models may consider excluding the risk adjusters SES and SOI as well and face the trade-off between reducing complexity but increasing selection incentives. While the specific policy choices and data differ across countries, the general patterns and conclusions presented in this thesis may provide useful insights for policymakers in other countries. However, the practical implications depend on the policies of each country.

6.4 Overall conclusion

This thesis shows that while the risk adjusters SES and SOI have a limited contribution to the statistical performance of the Dutch risk equalization model for somatic care, these risk adjusters still play an important role in reducing selection incentives for vulnerable subgroups. Most of the variation these risk adjusters can explain is already captured by other risk adjusters in the current risk equalization model, as demonstrated by the differences between the potential and net contributions. However, the analysis shows that SES and SOI are valuable in reducing selection incentives for vulnerable subgroups, particularly for individuals in the SOI classes completely unable to work, partly unable to work, and social assistance beneficiaries, as well as SES class 1 (very low). Therefore, policymakers face a trade-off between reducing the complexity of the risk equalization model and limiting the effect on selection incentives. Policymakers may consider retaining certain specific risk classes of SES and SOI, rather than excluding the entire risk adjuster. Since the analysis in this thesis is based on a sample rather than on the full population covered by the Dutch health insurance act, and OLS regression is used instead of constrained regression, future research is needed to more definitively inform policy decisions regarding these risk adjusters.

7. Reference list

- Bauhoff, S. (2012). Do health plans risk-select? An audit study on Germany's Social Health Insurance. *Journal Of Public Economics*, 96(9–10), 750–759. <https://doi.org/10.1016/j.jpubeco.2012.05.011>
- Duijmelinck, D. M., & van de Ven, W. P. (2014). Choice of insurer for basic health insurance restricted by supplementary insurance. *The European journal of health economics : HEPAC : health economics in prevention and care*, 15(7), 737–746. <https://doi.org/10.1007/s10198-013-0519-7>
- Eijkenaar, F., van Vliet, R. C. J. A., & van Kleef, R. C. (2019). Risk equalization in competitive health insurance markets: Identifying healthy individuals on the basis of multiple-year low spending. *Health services research*, 54(2), 455–465. <https://doi.org/10.1111/1475-6773.13065>
- Enthoven, A.C. (1988). Managed competition of alternative delivery systems. *Journal of Health Politics Policy and Law*, 13(2), 305–321. <https://doi.org/10.1215/03616878-13-2-305>
- Enthoven, A. C. (1993). The history and principles of managed competition. *Health Affairs*, 12 (suppl 1), 24–48. https://doi.org/10.1377/hlthaff.12.suppl_1.24
- Hamstra, G., Borg, S., Suurenbroek, P., & Stam, P. (2023). *Complexiteit in de uitvoering van de risicoverevening: Eindrapportage*. Equalis Strategy & Modeling B.V.
- Layton, T. J., Ellis, R. P., McGuire, T. G., & Van Kleef, R. (2017). Measuring efficiency of health plan payment systems in managed competition health insurance markets. *Journal Of Health Economics*, 56, 237–255. <https://doi.org/10.1016/j.jhealeco.2017.05.004>
- Layton, T.J., Ellis, R.P., McGuire T.G. & van Kleef R.C. (2018). Evaluating the performance of health plan payment systems. In McGuire T. G., van Kleef R. C. (Eds.), *Risk adjustment, risk sharing and premium regulation in health insurance markets: theory and practice* (pp. 133–167). Elsevier Publishing
- McGuire, T.G. & Van Kleef R.C. (2018). Regulated competition in health insurance markets: paradigms and ongoing issues. In McGuire T. G., van Kleef R. C. (Eds.), *Risk adjustment, risk sharing and premium regulation in health insurance markets: theory and practice* (pp. 3-20). Elsevier Publishing
- McGuire, T. G., Zink, A. L., & Rose, S. (2021). Improving the performance of risk adjustment systems. *American Journal of Health Economics*, 7(4), 497–521. <https://doi.org/10.1086/716199>
- Ministerie van Volksgezondheid, Welzijn en Sport (VWS). (2017). *Beschrijving van het risicovereveningssysteem van de Zorgverzekeringswet 2017*. Den Haag: Ministerie van Volksgezondheid, Welzijn en Sport.
- Ministerie van Volksgezondheid, Welzijn en Sport (VWS). (2024). *Regeling risicoverevening 2025 (concept)*. Staatscourant, Nr.31526.
- Newhouse, J. P. (1996). Reimbursing Health Plans and Health Providers: Efficiency in Production Versus Selection. *Journal of Economic Literature*, 34(3), 1236–1263. <http://www.jstor.org/stable/2729501>

Nivel (2022). Nivel Zorgregistraties. 2022. NZR-00322.052.

PricewaterhouseCoopers Advisory N.V. (2006). *Beschrijving besluitvormingsproces risicoverevening Zorgverzekeringswet*.

Stam, P., Hamstra, G., Hoekstra, R., Gerrits, R. (2021). *Doelen en uitgangspunten van de risicoverevening, een eerste stap naar consensus met de begeleidingscommissie*. Equalis Strategy & Modeling B.V.

Van de Ven, W. P., Beck, K., Buchner, F., Schokkaert, E., Schut, F., Shmueli, A., & Wasem, J. (2013). Preconditions for efficiency and affordability in competitive healthcare markets: Are they fulfilled in Belgium, Germany, Israel, the Netherlands and Switzerland? *Health Policy*, 109(3), 226–245. <https://doi.org/10.1016/j.healthpol.2013.01.002>

Van de Ven, W. P., & Ellis, R. P. (2000). Chapter 14 Risk adjustment in competitive health plan markets. In *Handbook of health economics* (pp. 755–845). [https://doi.org/10.1016/s1574-0064\(00\)80173-0](https://doi.org/10.1016/s1574-0064(00)80173-0)

Van de Ven, W., Hamstra, G., van Kleef, R., Reuser, M., & Stam, P. (2023). The goal of risk equalization in regulated competitive health insurance markets. *The European journal of health economics: HEPAC : health economics in prevention and care*, 24(1), 111–123. <https://doi.org/10.1007/s10198-022-01457-7>

Van de Ven, W.P.M.M. and Van Kleef, R.C. A critical review of the use of R^2 in risk equalization research. (2025). *Eur J Health Econ* 26, 363–375. <https://doi.org/10.1007/s10198-024-01709-8>

Vanhommerig JW, Verheij RA, Hek K, et al. Data Resource Profile: Nivel Primary Care Database (Nivel-PCD), *The Netherlands*. *International Journal of Epidemiology*, 2025, 54(2), dyaf017 <https://doi.org/10.1093/ije/dyaf017>

Van Kleef, R.C., Eijkenaar, F., Van Vliet, R.C.J.A., 2017. Risicoverevening 2016: Uitkomsten op subgroepen uit de Gezondheidsmonitor 2012.

Van Kleef, R. C., Eijkenaar, F., & Van Vliet, R. C. J. A. (2019). Selection incentives for health insurers in the presence of sophisticated risk adjustment. *Medical Care Research and Review*, 77(6), 584–595. <https://doi.org/10.1177/1077558719825982>

Van Kleef R. C., Eijkenaar F., van Vliet R. C. J. A., & van de Ven W. P. M. M. (2018). Health plan payment in the Netherlands. In McGuire T. G., van Kleef R. C. (Eds.), *Risk adjustment, risk sharing and premium regulation in health insurance markets: theory and practice* (pp. 397–430). Elsevier Publishing

Van Kleef, R. C., McGuire, T. G., Van Vliet, R. C. J. A., & Van de Ven, W. P. P. M. (2016). Improving risk equalization with constrained regression. *The European Journal of Health Economics*, 18(9), 1137–1156. <https://doi.org/10.1007/s10198-016-0859-1>

Van Kleef, R.C., Reuser, M., Stam, P. J., & Van de Ven, W. P., (2022), Positive and negative effects of risk equalization and risk sharing in regulated competitive health insurance markets, *EsCHER Working Paper Series No, 2022014*, Erasmus University Rotterdam. <https://www.eur.nl/en/research/escher/research/working-papers>

Van Kleef, R. C., Reuser, M., Stam, P. J., & Van de Ven, W. P. (2024). A framework for ex-ante evaluation of the potential effects of risk equalization and risk sharing in health insurance markets with regulated competition. *Health Economics Review*, 14(1).
<https://doi.org/10.1186/s13561-024-00540-4>

Van Kleef, R.C & Van Vliet, R.C. J. A. (2025). *Evaluatie risicoverevening 2024 & 2025*. Erasmus School of Health Policy & Management (ESHPM).

Van Kleef, R. C., Van Vliet, R. C., & Van de Ven, W. P. (2013). Risk equalization in The Netherlands: an empirical evaluation. *Expert review of pharmacoeconomics & outcomes research*, 13(6), 829–839. <https://doi.org/10.1586/14737167.2013.842127>

Withagen-Koster, A. A., Van Kleef, R. C., & Eijkenaar, F. (2022). Selection incentives in the Dutch basic health insurance: To what extent does End-of-Life spending contribute to predictable profits and losses for selective groups? *Medical Care Research and Review*, 79(6), 819–833.
<https://doi.org/10.1177/10775587221099731>

WOR 1234. Toetsingskader 2024 en verder; 2024. Den Haag: ministerie van VWS.

8. Appendix 1

Table A.1.: Mean financial result in 2022 for subgroups under different simulated models and the current risk equalization model of 2025 when constrained regression was used ^{A,B}

	Model 0 (Without any risk adjusters)	Model 1 (Only includes risk adjusters SES and SOI)	Model 2 (The current risk equalization model)	Model 3 (The current risk equalization model excluding SES and SOI)	The current 2025 risk equalization model using constrained regression
SES class					
Very low	-819	0	0	-56	18
Low	-81	0	0	10	20
Middle	194	0	0	9	-8
High	466	0	0	25	-23
SOI class					
Completely unable to work	-5319	0	0	-381	203
Partly unable to work	-1817	0	0	-252	87
Social assistance beneficiaries	-437	0	0	-265	-63
Students	1752	0	0	39	-57
Self- employed individuals	1243	0	0	87	-53
Highly educated individuals	1282	0	0	85	-62
Reference group	9012	0	0	22	-30
70+	-4086	0	0	0	154

^A Results are based on the 2021 Nivel-PCD and on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B SES is Socioeconomic Status; SOI is Source of Income

9. Appendix 2

Table A.2.: Total financial result in 2022 under model 2 (the current risk equalization model), model 3 (the current risk equalization model excluding SES and SOI, and the absolute difference between these models ^{A,B, C}

	Total financial result model 2 (the current risk equalization model)	Total financial result model 3 (the current risk equalization model excluding SES and SOI)	Difference in total financial result between model 2 and 3
At least one chronic condition			
Yes (59.3 %)	551,606,062	569,227,007	17,620,945
No (40.7 %)	-551,576,373	-569,226,816	-17,650,444
Social disability (0.5 %)	-46,695,434	-47,606,376	-910,942
Cancer (8.5 %)	-364,199,973	-359,825,956	4,374,017
Diabetes (6.3 %)	-113,980,226	-116,544,863	-2,564,636
Coronary heart disease (3.2 %)	-46,695,434	-47,606,376	-910,942
COPD (2.9 %)	-157,005,401	-161,698,332	-4,692,931
SES class			
1 very low (21.7 %)	0	-209,193,328	-209,193,328
2 low (19.6 %)	0	34,543,514	34,543,514
3 middle (29.4 %)	0	45,244,085	45,244,085
4 high (29.3 %)	0	129,410,958	129,410,958
Source of income			
Completely unable to work (1.1 %)	0	-74,726,295	-74,726,295
Partly unable to work (5.3 %)	0	-231,894,511	-231,894,511
Social assistance beneficiaries (3.9 %)	0	-180,097,800	-180,097,800
Students (4 %)	0	26,590,082	26,590,082
Self-employed individuals (10.2 %)	0	153,601,034	153,601,034
Highly educated individuals (7.1 %)	0	104,436,373	104,436,373
Reference group (53.7 %)	0	202,124,571	202,124,571
70+ (14.6 %)	0	0	0

^A Results are based on the RE-dataset which contains individual level data on medical spending and information on all the risk adjuster for 2022, and are reweighted to reflect the full population insured under the Dutch health insurance act, excluding non-residents.

^B Percentages reflect the prevalence relative to the population insured under the Dutch health insurance act in 2022, excluding non-residents.

^C SES is Socioeconomic Status; SOI is Source of Income