Thesis

Mental Healthcare and Risk Equalization

Assessing the contribution of morbidity indicators in the Dutch RE model

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Abstract

The aim of this study is to examine the extent to which the morbidity indicators in the Dutch risk equalization (RE) model for mental care – diagnoses-based cost groups (DCGs), pharmacy-based cost groups (PCGs) and multiple-year high-cost groups (MYHCs) – identify subgroups with specific chronic mental diseases. The Dutch RE model is still imperfect and therefore substantially over/undercompensates subgroups with specific chronic conditions, which incentivizes insurers for risk selection. Therefore, it is important to study the role of the morbidity indicators and their contribution to possible over- and undercompensation of specific subgroups. By doing a quantitative simulation study, using Dutch health insurance data and General Practitioner's morbidity data from Nivel Primacy Care Database, specific subgroups with chronic mental diseases were analyzed through different steps. For these subgroups the contribution of the morbidity indicators to identifying these chronic diseases and the mean financial result was calculated, indicating over- and undercompensation. Findings show that many individuals with a chronic mental disease are not identified by the morbidity indicators, leading to systematic undercompensation of these subgroups. This study concludes that improved identification by morbidity indicators in the RE model for mental care is essential to ensure sufficient compensation and reduce selection incentives. Additionally, results highlight that even for identified parts of subgroups, compensation is not always accurate, suggesting the need for more refined or condition-specific adjusters in the model.

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1. Problem analysis and research questions

In 2006, the Dutch government introduced a fundamental reform of the health insurance system. During this reform, the Health Insurance Act was implemented, a private social insurance scheme (CBS, 2015). Regulated competition was introduced, which made private health insurers responsible for providing mandatory insurance for every Dutch citizen by competing in terms of price and quality (Schut & Varkevisser, 2016).

The Dutch healthcare system is based on the model of managed competition of Enthoven (1988), which aims to pursuit equity and efficiency in healthcare by encouraging cost-conscious consumer choice among health plans. It views the healthcare market as "three-cornered", including consumers, health plans and sponsors. In most European countries, such as the Netherlands, the government acts as the sponsor and strongly regulates the health insurance market (Heinemann et al., 2013). The Health Insurance Act enforces accessibility and affordability of health plans through a community-rated premium, open enrollment, and a ban on premium differentiation (Kroneman et al., 2016). The latter prevents insurers from charging a higher premium for high-risk individuals (Nederlandse Zorgautoriteit, 2025).

Healthcare is not a typical economic good and therefore *unregulated* competition is likely to result in market failure, particularly risk selection (Fielding & Rice, 1993). Risk selection can occur when "health risks" or expected medical costs are unevenly distributed among different health plans (Enthoven, 1988). Since insurers cannot differentiate premiums, they have an incentive to attract low-risk consumers instead of high-risk consumers (Van de Ven et al., 2000). To counteract incentives for risk selection, a risk equalization (RE) model was introduced. In the Netherlands, the RE model compensates insurers for the predictable variation in individual medical expenses between low- and high-risk individuals (Van Kleef et al., 2013b). The Dutch RE system consists of three different equalization models for somatic care, mental care and out-of-pocket payments due to the mandatory deductible (Van Kleef et al., 2018).

The characteristics of insured individuals that are used to compensate insurers are called risk adjusters. At first, the only risk adjusters in the RE models were sex and age, but throughout the years several risk adjusters were added. This thesis will focus on the morbidity indicators used in the model for mental healthcare: diagnoses-based cost groups (DCGs), pharmacy-based cost groups (PCGs) and multiple-year high-cost groups (MYHCs) (Stam et al., 2010). DCGs are based on specific diagnoses from the previous year, PCGs are based on

an individual's prior use of pharmaceuticals and MYHCs are based on healthcare spending in the previous years (Ministerie van VWS, 2024a).

Despite sophisticated risk equalization, research indicates that the current model is still imperfect and therefore incentivizes insurers for risk selection (Withagen-Koster et al., 2024). Earlier studies in the field are mainly focused on the RE model for somatic care. However, recent research by van Kleef & van Vliet (2025) has shown that the RE model for mental care still leads to undercompensation of subgroups with specific mental diseases. A potential reason for this undercompensation may be that the morbidity indicators in the RE model insufficiently identify individuals with a chronic mental disease (Van de Ven et al., 2022).

Whilst assessing the contribution of the morbidity indicators to identifying subgroups with specific chronic conditions, it is important to determine to what extent the undercompensation is due to non-identification of specific subgroups. The more effectively the RE model compensates insurers for predictable variation, the lower the risk of risk selection (Van Veen, 2016). Hence, the research question of this paper is:

To what extent do the morbidity indicators in the Dutch risk equalization model for mental healthcare compensate insurers for the expected spending of subgroups with specific chronic mental diseases?

This paper aims to answer this question based on the following sub questions:

- To what extent do the morbidity indicators DCG, PCG and MYHC in the RE model for mental care identify individuals with specific chronic mental diseases?
- To what extent does the risk equalization model for mental care compensate insurers for the expected spending of individuals with specific chronic mental diseases who are identified by DCG, PCG and/or MYHC?
- To what extent does the risk equalization model for mental care compensate for the expected spending of individuals with specific chronic mental diseases who are ***not*** identified by DCG, PCG and/or MYHC?

By addressing this research question, this study could contribute to the evaluation and development of the Dutch RE model for mental care, particularly if it concludes that certain chronic mental diseases are not accurately identified by the current model. These insights can help improve the Dutch RE model and counteract incentives for risk selection. Furthermore, countries like Belgium, Germany, Israel, Switzerland and the U.S., have introduced

(principles of) regulated competition among insurers (Van De Ven et al., 2007). Currently, the Dutch model is one of the most sophisticated RE models worldwide (Stam et al., 2010). Studying the role of morbidity indicators in the Dutch RE model could provide valuable insights for improving RE models in these countries as well.

In this thesis, first the theoretical framework will provide information on the Dutch health insurance system, the RE model within this system, including the morbidity indicators and the performance of the model. Second, the used research methods will be discussed, using different steps of data analysis. The result section will then follow the same steps to discuss the results of the analyses and provide an answer to the different sub questions. In the discussion the answers to the different sub questions are discussed, including their contribution to the existing literature. Also, the strengths and limitations of this research, recommendations for further research and policy implications are mentioned. Lastly, an answer to the research question will be provided.

2. Theoretical framework

This chapter begins by outlining the health insurance system in the Netherlands, its financing, and the international context, followed by the goals of the RE model within this system. Then, the RE model itself is explained, including its risk adjusters, with a focus on the morbidity indicators in the RE model for mental care. Finally, the performance of the model is discussed.

2.1 Health insurance system of the Netherlands

As mentioned in the introduction, in 2006 the Netherlands implemented the Health Insurance Act: a mandate for every Dutch citizen to buy a basic benefits package from a private health insurer, based on principles of regulated competition (Van de Ven & Schut, 2009). About 15 competing insurers are intended to be the prudent buyers of care and have to offer a standardized basic benefits package that is determined by the government (Schut & Varkevisser, 2016). Insurers negotiate with healthcare providers about the price, volume and quality of care and are allowed to contract selectively to promote efficiency in the delivery of care. Moreover, insurers must make sure that services are available to the consumer within a reasonable travel and waiting time to safeguard the accessibility of care. To protect public interests, the government sets regulations ensuring individuals have access to affordable health plans (Van Kleef et al., 2018). Consumers are annually free to choose among all basic health plans offered by these insurers. Contracts start on January 1st and have a maximum duration of one year. Consumers have several options when choosing a health plan, including selecting an insurer, determining the level of voluntary deductible and considering the network of contracted providers along with out-of-network coverage (Van Kleef et al., 2018). The level of voluntary deductible allows consumers to raise their deductible above the mandatory minimum of 385 euros. A higher deductible results in a greater discount on the premium. Additionally, consumers can voluntarily purchase supplementary health insurance, like dental care for adults, physiotherapy and alternative medicines (Van Winssen et al., 2015). However, these are not covered under the Health Insurance Act.

Mental care is included in the basic benefits package under certain conditions: a minimal age of 18 years, a mental disorder classified under the DSM-5 (Diagnostic and Statistical Manual of Mental Disorders) and the treatment must meet the ‘standard of science and practice’ (Ministerie van VWS, 2025). The DSM-5 is a professional guide that divides mental conditions into different categories. The ‘standard of science and practice’ means that

there must be sufficient evidence that the treatment is effective, which is determined by the insurer (Ministerie van VWS, 2025). In some cases, mental care is not covered under the Health Insurance Act, but under the Long-Term Care Act. The Long-Term Care Act is intended for individuals with a condition that requires continuing intensive care (Ministerie van VWS, 2024e).

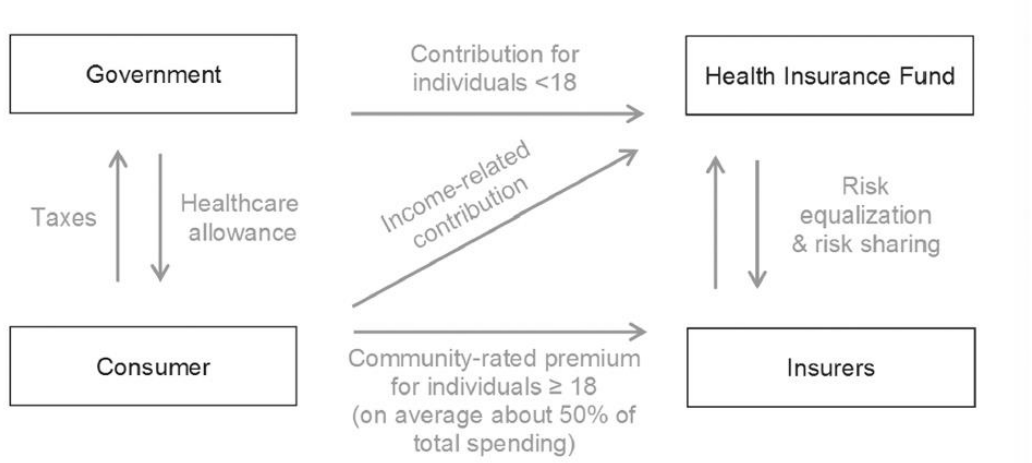
2.1.1 Financing of the Health Insurance Act

The Dutch healthcare system is financed according to principles of solidarity. Solidarity refers to a social cohesion among individuals and is established in healthcare by public social insurance arrangements of the government (Meijer et al., 2023). Individuals pay mandatory contributions in exchange for financial support in case of illness. These contributions are in part related to income; people with higher incomes contribute more (income solidarity), and to risk (risk solidarity). Risk solidarity refers to the government's effort to establish cross-subsidies from healthy individuals to the sick (Van Kleef et al., 2018).

In figure 1 the financing scheme of the Health Insurance Act is illustrated. The government organizes a Health Insurance Fund with mandatory contributions from taxes, employers, insurers and consumers. Every Dutch individual above 18 years pays a community-rated premium to their insurer and for individuals younger than 18 years, the government pays a contribution to the Health Insurance Fund (Van Veen, 2016). Annually, this community-rated premium is determined by the Ministry of Health and is the same for all insured individuals (Ministerie van VWS, 2017). However, this premium is considered being too high for low- and middle-income individuals and therefore they receive an income-related premium subsidy, financed with general tax revenues (Van Kleef et al., 2018). Also, an income-related contribution is paid to the Health Insurance Fund, partly by the consumer and partly by their employer.

Subsequently, the money from the Health Insurance Fund is allocated among insurers via the risk equalization system (Van Veen, 2016). Chapter 2.3 provides a detailed explanation of how the risk equalization payment is determined.

Figure 1. Financing scheme Health Insurance Act.



Source: Van Kleef et al. (2018).

2.1.2 International context

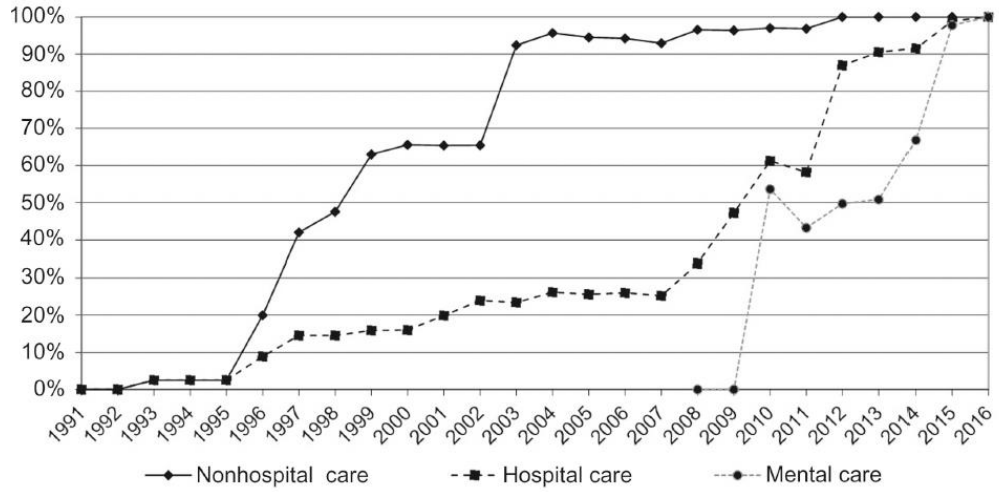
The Netherlands is not the only country with a health insurance system based on regulated competition. As mentioned in the introduction, Belgium, Germany, Israel, Switzerland and the U.S., have also introduced (principles of) regulated competition among insurers (Van de Ven et al., 2007). Despite varying paths of reform, these systems share common objectives of access, financing and efficiency in both health insurance products and healthcare provision (McGuire & Van Kleef, 2018). All these countries have implemented a risk equalization system, though some are more successful than others to counteract incentives for risk selection (Van de Ven et al., 2007). However, they all face the challenge of evaluating and improving their RE models (Van Kleef et al., 2018). Therefore, findings of this research may contribute to improving the RE models across these countries as well.

2.2 Goals of risk equalization

Risk equalization compensates health insurers based on the risk profile of the insured, aiming to establish a level playing field among insurers by removing predictable profits and losses resulting from the ban on premium differentiation (Ministerie van VWS, 2017). Many countries with regulated competitive health insurance markets, like the Netherlands, have implemented a RE model and are continuously improving it (Van de Ven et al., 2022). Risk equalization in the Netherlands is implemented through an ex-ante system, which means that the compensation provided to the insurers is established before the start of the calendar year to which it applies. With ex-ante risk equalization, the insurer bears financial risk (Ministerie

van VWS, 2017). As the risk equalization model improved, the financial risk for insurers increased. Now they almost bear full financial risk for all types of care, which is visible in figure 2 (Van Kleef et al., 2018). This shift occurred as the level of ex-post cost-compensation for insurers declined, transitioning from compensation based on actual costs to compensation based on predicted costs (Van Kleef et al., 2014). The transition from ex-post cost-compensation to ex-ante risk equalization was driven by the reduction of efficiency incentives for insurers (Beekman & Van der Lee, 2022). Since 2016, the financial risk for insurers has not changed substantially. Mental care was transferred to the Health Insurance Act in 2008, making insurers increasingly financial responsible for this type of care from that year onward.

Figure 2. Financial risk for insurers in the period 1993-2016.



Note. The period between 1991 – 2005 refers to the Sickness Fund Scheme, which was the prevailing health insurance scheme during that time. The period from 2006 to 2016 relates to the Health Insurance Act.
Source: Van Kleef et al. (2018).

Financial risk for insurers increases incentives for efficiency, but it also creates incentives for risk selection. Risk selection is defined by Van Kleef et al. (2013) as *"actions by consumers and insurers with the intention and/or the effect that the costs of low-risk and high-risk individuals are not fully pooled"*. As explained before, in the Dutch basic health insurance there are instruments that are intended to stimulate efficiency, like free consumer choice of health plan, a community-rated premium and a mandatory/voluntary deductible. However, these instruments can also be used or may result in risk selection. Due to imperfections of the RE model, attracting low-risk individuals remains financially beneficial for insurers (Van Kleef et al., 2013a). A possible form of risk selection in Dutch health insurance is product differentiation (Van Kleef et al., 2014). Although the basic benefits package is standardized,

there are still possibilities for product differentiation through the coverage level, quality level, service level, contract period and additional terms of health plans (Van Kleef et al., 2013a). Another form of risk selection is selective advertising and marketing by insurers. By selectively promoting their health plans, insurers focus on attracting specific low-risk groups, such as college students. Risk selection also occurs in supplementary health insurance, which is chosen by nearly 85% of the Dutch population (Van Kleef et al., 2013a). Since supplementary health insurance is unregulated, insurers are allowed to reject coverage to high-risk applicants. As a result, these high-risk individuals are likely to obtain basic insurance from a different insurer.

Specifically for mental care – where a small part of the population accounts for the high spending – insurers face a strong incentive to engage in risk selection. Only 0.8% of the Dutch population is responsible for 66% of annual mental health spending, so individuals who use mental health services are likely to generate financial losses for insurers (Beekman & Van der Lee, 2022). As a result, having a strong reputation in purchasing high-quality mental care can pose a financial risk for insurers.

Consequently, risk selection can have negative effects, like the reduction of solidarity between low-risk and high-risk individuals (Van de Ven & Ellis, 2000). Other potential negative effects of risk selection are the absence of a level playing field for providers and suboptimal consumer-service for high-risk consumers. Even a reduction of (investments in) the quality of care, because insurers and providers do not strive for obtaining the best reputation for treating high-risk individuals (Van Kleef et al., 2024). Recent evidence suggests that Dutch health insurers indeed engage in risk selection, highlighting the need for further improvements of the RE model (Withagen-Koster et al., 2024).

2.3 Risk equalization model

As mentioned in the introduction, the Dutch RE model consists of three different models. A model for somatic care, mental care and for out-of-pocket payments due to the mandatory deductible (Ministerie van VWS, 2024a). The model for out-of-pocket payments is not relevant for this paper. The model for somatic care and the model for mental care share certain risk adjusters but also have system-specific risk adjusters. Once short-term mental care was transferred to the Health Insurance Act in 2008, there were specific risk-sharing mechanisms applied to this type of care. Hence, two separate models were needed. These risk-sharing mechanisms do not exist anymore, but the two models are still separated (Van Kleef

et al., 2018). The model for mental care is only applicable to individuals of 18 years and older. Mental healthcare for minors is not financed through the Health Insurance Act, but under the Youth Act (Ministerie van Algemene Zaken, 2024). The risk adjusters that are integrated in the RE model 2025 for mental healthcare are listed in Table 1, including the amount of risk classes and a short description per risk adjuster.

Table 1. Risk adjusters in the Dutch RE model for mental care.

Risk adjusters	**Risk classes**	**Short description**
Age interacted with gender	30	Age in interaction with gender.
Pharmacy-based cost groups (PCGs) mental diseases	9+1	Based on individual's prior use of pharmaceuticals, specifically for mental diseases. Plus, a risk class for no PCG.
Diagnose-based cost groups (DCGs) mental diseases	16+1	Specific mental diagnoses from the previous year. Plus, a risk class for no DCG.
Source of income	29	Source of income/education in interaction with age. Categories: - *Permanently and fully incapacitated for work* - *Partially incapacitated for work* - *Social assistance recipient* - *Students* - *Self-employed individuals* - *Highly educated individuals* - *Reference group*
Zip-code clusters for mental care	10	Based on the four digits of the zip-code and the relation between mental care spending and information at regional level.
Socioeconomic status (SES)	8	Based on household income in interaction with age.
Number of persons per address (PPA)	12	Based on long-term care use in interaction with age.
Multiple-year high-cost groups (MYHCs) mental care	7+1	Based on mental healthcare spending in the previous years. Plus, a risk class for no MYHC.
Seasonal workers*	3	Based on place of residence.

Note. The RE model for mental care is only applicable for individuals of 18 years and older.
**The risk adjuster seasonal workers is not included in the dataset.*
Source: Ministerie van VWS (2024a).

All risk classes take the form of dummy-variables indicating whether an individual is picked up by a certain risk class (Van Kleef et al., 2018). In the RE model, each value of a risk adjuster is assigned a 'payment weight'. These payments weights represent the mean additional cost for individuals in a risk class while considering all other risk classes in the RE model. The payment weights for year *t* follow from an individual-level regression of medical

spending in year *t-3* on the dummy variables from year *t-3* (Van Kleef et al., 2018). Before estimation some modifications must be applied to make the data representative for year *t*. First, this is done by adjusting the number of individuals in each risk class for year *t-3* to align with the projected prevalence for year *t* through a reweighting process. Then the spending from year *t-3* is corrected to account for specific system changes between *t-3* and *t*, like updates to the basic benefit package and cost inflation. After these adjustments, the total spending in the dataset matches the government's projected total spending for year *t* (Van Kleef et al., 2018).

Subsequently, a restricted least-squares regression model is used to calculate the predicted costs based on all risk adjusters. A restricted least-squares regression is used instead of an ordinary least-squares regression to avoid negative predictions of medical spending that can occur in a multivariate regression (Ministerie van VWS, 2017). This regression is based on annual spending weighted by the fraction of the year and individuals enrolled in *t-3.* This can be less than a full year, due to birth, death or migration (Van Kleef et al., 2018).

The risk equalization payment an insurer receives from the Health Insurance Fund for individuals aged 18 years and older equals the predicted spending for somatic and mental care minus the predicted out-of-pocket spending due to the mandatory deductible and the community-rated premium. For individuals younger than 18 years, the contribution from the Health Insurance Fund is equal to their predicted healthcare spending. Every year, the RE models are re-estimated as new data becomes available. The Ministry of Health leads a program to improve the models, which results every year in changes in terms of risk adjuster variables (Van Kleef et al., 2018). This paper specifically focuses on the morbidity indicators in the RE model for mental care. Therefore, these indicators will be further explained in the next paragraphs.

2.4 Morbidity indicators

Morbidity indicators are risk adjusters derived from (prior) healthcare utilization and expenses. The morbidity indicators in the RE model are mostly based on information through hospital treatments and drug prescriptions (Oskam et al., 2023). The Dutch RE model for mental care consists of three morbidity indicators: diagnoses-based cost groups, pharmacy-based cost groups and multiple-year high-cost groups (Van Kleef et al., 2014).

2.4.1 Diagnoses- based cost groups (DCG)

Since 2004, the Dutch RE model includes diagnoses-based cost groups (DCGs) (Van Kleef et al., 2013c). DCGs primarily rely on diagnostic information from specific treatments in the previous years. When determining DCGs, only diagnoses for conditions are included which are expected to lead to relatively high costs in the following year (Ministerie van VWS, 2017). DCGs for mental care in 2025 are based on diagnose information from the years 2022, 2023 and 2024 and consist of different risk classes. Next to the category "No DCG mental diseases", 16 other categories are distinguished, based on expected costs (Ministerie van VWS, 2024). Examples of mental diagnoses included in DCGs are schizophrenia, addiction and personality disorder (Ministerie van VWS, 2024c). Treatments for different diseases can be classified into the same DCG, because of similar predicted costs in the following year. According to the Ministry of Health (2024a) only single DCGs for mental care are considered. This means that an insured individual who has received multiple relevant treatments, is ultimately classified into a single DCG (the most severe one). Eijkenaar et al. (2018) suggest that the RE model can potentially be improved by allowing classification in multiple DCGs instead of one.

2.4.2 Pharmacy-based cost groups (PCG)

Pharmacy-based cost groups (PCGs) aim to recognize insured individuals with a certain chronic condition by claims for medications known to be prescribed for that condition. PCGs are based on the use of medicines in the previous year. Someone is placed in a PCG if more than a specified number of certain medications was prescribed in that year (Ministerie van VWS, 2017). The RE model 2025 consists of nine PCGs for mental conditions and a category for individuals without a PCG. Individuals are included in all applicable PCGs (Ministerie van VWS, 2024a). The PCGs included in the RE model for mental care are use of medication for ADHD, addiction (excluding nicotine), anxiety disorders, chronic mood disorders (regular), chronic mood disorders (complex), bipolar disorders (regular), bipolar disorders (complex), psychosis and psychosis (depot) (Ministerie van VWS, 2024d).

2.4.3 Multiple-year high-cost groups (MYHC)

Insured individuals with high healthcare expenses over the years have a higher chance of making high costs again in the next year, therefore the risk adjuster multiple-year high-cost

groups (MYHC) is included in the RE model for mental care since 2020 (Ministerie van VWS, 2019). MYHC is based on costs of the five previous years (Ministerie van VWS, 2017). The underlying assumption is that individuals with multiple-year high-costs most likely suffer from a chronic condition (Withagen-Koster et al., 2018).

Insured individuals with a high-cost history are classified in different categories. These categories differ between people that had high spending during the total of five years and people who had at least two times high spending during a period of five years (Ministerie van VWS, 2024a). Because of their short medical history, for insured individuals younger than 24 years applies that they had at least once high spending on mental care in the previous five years. There is also a category for people who did not exceed the threshold for medical spending on mental care: "No mental care-MYHC". The risk classes of the risk adjuster MYHC in 2025 are listed in table 2.

Table 2. Risk classes of the risk adjuster MYHC in the RE model 2025.

Risk classes MYHC 2025
No mental-care MYHC
At least 1 of the previous 3 years mental care costs in the top 98.5% with mental care spending > 10 euros.
At least 2 of the previous 5 years mental care costs in the top 1%*.
At least 2 of the previous 5 years mental care costs in the top 0.5%*.
At least 2 of the previous 5 years mental care costs in the top 0.25%*.
At least 2 of the previous 5 years mental care costs in the top 0.1%*.
Mental care costs in the top 0.5% for all 5 of the previous years.
Mental care costs in the top 0.25% for all 5 of the previous years.

**Note. For insured individuals younger than 24 years, at least 1 of the previous 5 years applies.*
Source: Ministerie van VWS (2024a).

2.5 Performance of the risk equalization model

As mentioned, the goal of the RE model is to counteract incentives for risk selection by insurers. Withagen-Koster et al. (2024) conclude that there is evidence that Dutch insurers indeed do engage in risk selection. On top of that, recent studies have demonstrated that even the sophisticated Dutch RE model fails to eliminate incentives for risk selection (Van Kleef et al., 2018; McGuire et al., 2020). Moreover, van Kleef & van Vliet (2025) conclude that for several subgroups with specific chronic diseases, there is a substantial over- or undercompensation. Especially, subgroups with specific chronic mental diseases are undercompensated by the current RE model for mental care. This highlights the need for further improvements of the RE model, specifically the RE model for mental care. Therefore,

it is important to keep evaluating the RE model to prevent from undercompensation of certain subgroups.

For evaluating the model, the Ministry of Health of the Netherlands has established an evaluation framework. This framework consists of several categories which are in line with the goals of the RE model: the equalization effect, efficiency, manageable complexity, validity, measurability and stability (Ministerie van VWS, 2024b). The equalization effect of the RE model refers to the extent to which the RE model compensates for differences in expected spending among low- and high-risk individuals. This provides an indication of the level playing field for insurers and the incentives for risk selection (Ministerie van VWS, 2024b). When adding a (risk class to a) risk adjuster or making a model change, the efficiency incentives for insurers must be considered. These incentives must be preserved to encourage efficient behavior among insurers. However, there are limits to the number of criteria and the addition of classes within the RE model, because it needs to be manageable. Furthermore, validity, measurability and stability are requirements for improving the RE model. These various elements of the evaluation framework should be considered in relation to each other (Ministerie van VWS, 2024b). This study focuses on measuring incentives for risk selection and on evaluating the model's validity. The latter is important for analyzing the contribution of the morbidity indicators in the RE model for mental care to identifying individuals with specific chronic mental diseases.

A lot of empirical evaluations have been performed to assess and compare incentives for risk selection of RE models over the years (Van Veen et al., 2015). In the overview provided by van Veen et al. (2015) of these evaluations conducted since 2000, identifying the R^2 is the most frequent used measure. The R^2 indicates the predictive performance of the set of risk adjusters. Van Veen et al. (2015) also mention the Cummins Prediction Measure (CPM) as a measure to evaluate the performance of the RE model. The CPM uses the absolute value of the difference between the predicted and actual values, meaning that positive and negative differences do not cancel each other out. The CPM is less sensitive to outliers than the R^2. Like the R^2, its value ranges between zero and one, with a value closer to one indicating higher predictive performance (Van Veen et al., 2015).

However, van de Ven & van Kleef (2024) conclude that the R^2 of RE models is difficult to interpret in the context of incentives for risk selection, making it an unsuitable measure for these incentives. Therefore, it is preferable to measure incentives for insurers that are more directly related to engaging in risk selection. Calculating over- and undercompensation for subgroups is identified as an adequate measure to assess incentives for

risk selection (Van Veen et al., 2015). Over- and undercompensation indicate the monetary value between predicted and actual spending of subgroups. If these measures are calculated for subgroups that are (potential) targets of risk selection, they provide meaningful insight into the incentives for insurers to engage in such actions (Van de Ven & Van Kleef, 2024). Moreover, Oskam et al. (2023) state that using over/undercompensation on the level of disease groups indicates adequate incentives for group-level selection. For measuring incentives for risk selection through over- and undercompensation, data is needed to identify relevant subgroups based on diagnose-information (Van Kleef & Van Vliet, 2025). Therefore, data from Nivel Primacy Care Database is used in this research, which will be further explained in chapter 3.

3. Research methods

To answer this paper's research question, a quantitative simulation study is conducted in Stata, using microdata on healthcare spending and characteristics of enrollees in the Dutch basic health insurance. This chapter first describes the data and data preparations. Thereafter, different steps of data analysis are explained. Lastly, validity and reliability of this study are discussed, including its limitations.

3.1 Data

For this study, a micro-dataset is used with general practitioner (GP) morbidity data from Nivel Primacy Care Database (Nivel-PCD). This data is collected from electronic health record systems from general practices with in total 1.2 million registered patients of 18 years and older (Vanhommerig et al., 2025). The data indicates whether a chronic disease was (1) or was not (0) registered for a patient in 2021, defined as 109 dummy-variables. These diagnoses are derived from the 'International Classification of Primary Care' (ICPC) and are based on the period between the date of diagnosis and the estimated date of recovery. The ICPC defines a chronic disease as an illness without any prospect of full recovery (Van Kleef & Van Vliet, 2025). In this study, the Nivel-PCD data is needed for the identification of relevant subgroups.

The Nivel-PCD dataset is enriched by the thesis supervisor with microdata collected by the Dutch Ministry of Health, necessary for simulating the RE model 2025. This individual-level microdata is derived from various administrative sources, including insurers, the tax collector and the registration service for social benefits. The data contains information on medical spending of Dutch citizens of 18 years and older with a basic health insurance in 2022. Medical spending is adjusted to be representative for the basic benefits package of 2025. Also, all risk adjusters of the RE model for mental care of 2025 are included in the dataset and defined as 130 dummy-variables. The risk adjuster *'seasonal workers'* is not included in the dataset and is therefore excluded from the analysis. Furthermore, a weighting factor, developed in previous research by van Kleef & van Vliet (2025), is included in the dataset. This factor ensures that the data more accurately reflects the entire Dutch population of 18 years and older with a basic insurance in 2022.

Table 3 provides an overview of the dataset, including the number of insured, the weighted number of insured and the mean actual mental care spending according to the RE model of 2022. Table 3 also shows the gender distribution across age categories and the proportion of individuals classified into at least one of the risk classes of the morbidity

indicators. It shows that 14.2% of the individuals in the dataset is identified by at least one risk class of DCG, PCG and/or MYHC. The subsequent rows show the percentages of individuals identified by each morbidity indicator separately. Out of the morbidity indicators, MYHC has the largest contribution to identifying chronically ill individuals in the dataset. There is likely to be overlap between the morbidity indicators, meaning some individuals fall into more than one risk class of the morbidity indicators.

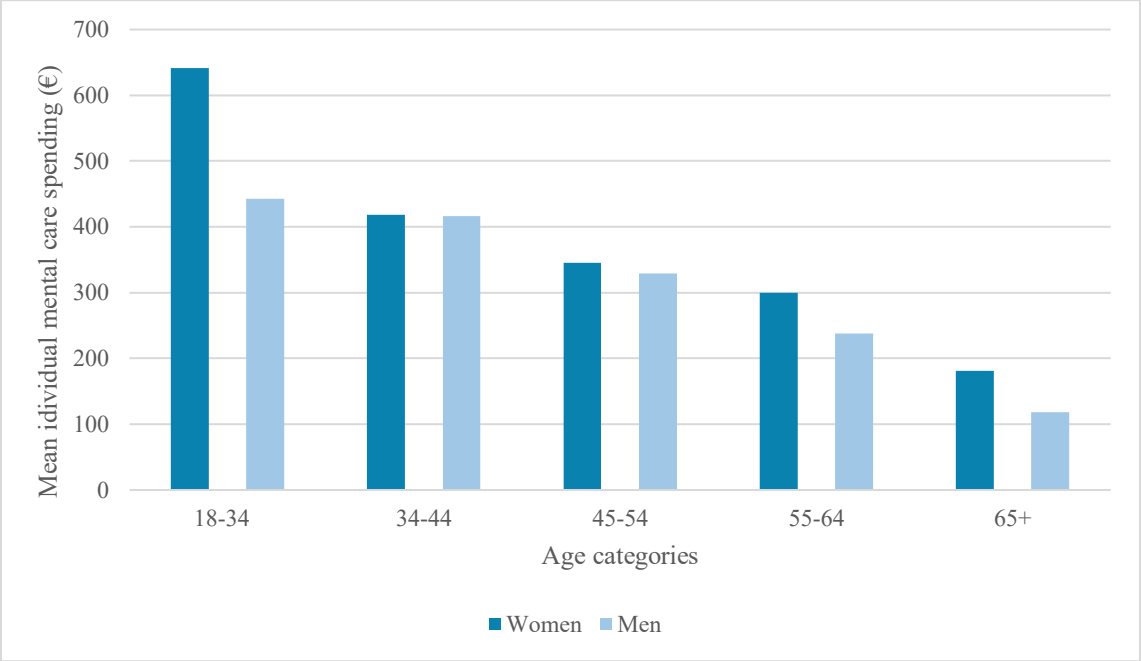
Table 3. Descriptive statistics of mental care spending and characteristics in 2022.

Number of insured	1,184,748
Weighted number of insured	14,044,432
Mean actual mental care spending (Y_i) 2022	€344.04
Men	49.1%
18-34 years	13.3%
34-44 years	7.4%
45-54 years	8.2%
55-64 years	8.6%
65 years and older	11.8%
Women	50.1%
18-34 years	13.0%
34-44 years	7.4%
45-54 years	8.3%
55-64 years	9.6%
65 years and older	13.5%
Individuals picked up by DCG, PCG and/or MYHC	14.2%
Individuals picked up by DCG	6.9%
Individuals picked up by PCG	5.6%
Individuals picked up by MYHC	10.5%

Note. Means of actual and predicted spending are presented per insured year. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset. DCG=diagnose-based cost groups, PCG=pharmacy-based cost groups and MYHC=multiple-year high-costs groups.

Additionally, figure 3 shows the distribution of individual mental care spending across the Health Insurance Act population. On the vertical axis the mean individual mental care spending is presented and on the horizontal axis the age categories per gender in the dataset are shown. This figure indicates that younger individuals have a higher mean mental care spending than older individuals. With every age category, the mean mental care spending declines. Individuals of 65 years and older have the lowest mental care spending. This contrasts with somatic care, where mean spending tends to increase with age (Withagen-Koster et al., 2023). In general, women have higher mean mental care spending than men, especially in the youngest age group between 18 and 34 years old.

Figure. 3. Mean mental healthcare spending per age group, for men and women in 2022.



Note. Figure relates to the Health Insurance Act population of 18 years and older in the weighted dataset.

3.2 Data analysis

To answer this paper's research question about the extent to which the morbidity indicators in the Dutch RE model for mental care compensate insurers for the expected spending of subgroups with specific mental diseases, five different steps of data analysis are conducted. The data analysis is performed in the secured CBS Microdata environment (CBS, n.d.), using Stata. The different steps are explained in the following paragraphs.

3.2.1 Step 1: Simulation risk equalization model for mental care 2025

During the first step, the dataset is used to simulate the RE model for mental care in 2025. Coefficients for the model are estimated by an ordinary least-squares (OLS) regression with mental health spending in 2022 as the dependent variable and the risk adjusters in the RE model for mental care 2025 as the independent variables. As explained in section 2.3, the actual RE model for mental care uses a restricted least-squares regression. However, due to the complexity of this approach, an OLS regression is used in this study. By performing an OLS regression in Stata, it is possible to determine the individual-level expected mental health costs ($\hat{Y}_i$) in 2025. Based on the regression coefficients, individual spending is predicted. Also, the R^2 of this model is reported, which indicates how much variance in the

mental health spending is explained by the risk adjusters in the model (Akossou & Palm, 2013). The formula of the R^2 (1) is formulated below, where Y_i indicates the actual spending of individual *i*, $\hat{Y}_i$ the predicted spending from the regression and $\bar{Y}$ the average spending in the population.

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

Additionally, the Cummings Prediction Measure (CPM) is calculated. The CPM replaces the squared discrepancies between the actual spending of individual *i* (Y_i), the predicted spending from the regression ($\hat{Y}_i$), and the average spending in the population ($\bar{Y}$), using the absolute value of the linear value before summing (Beck et al., 2020). The formula of this measure (2) is illustrated below.

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

3.2.2 Step 2: Identification of relevant subgroups

During this second step, the 109 chronic diagnoses from the Nivel-PCD data are used to identify relevant subgroups that may be over- or undercompensated with the current RE model. Out of the 109 dummy variables in the dataset, five relate to chronic mental diseases (category P). The variable names of these mental chronic diseases are listed in table 4, including the names of the mental conditions. Additionally, a variable was included to identify individuals with at least one chronic mental disease. In the result section, these subgroups are described in terms of their scope and average actual spending.

Table 4. Chronic mental diseases in the Nivel-PCD dataset.

Variable	Description
P28	Functional limitation/disability due to mental illness
P70	Senile dementia/Alzheimer's
P72	Schizophrenia
P80	Personality/character disorder
P85	Mental retardation/intellectual disability

Source: Nivel. (2022).

3.2.3 Step 3: Examining the contribution of the morbidity indicators

For answering the first sub question, the percentage of individuals with a specific mental disease that is identified by DCG, PCG and/or MYHC is calculated. In addition, the morbidity indicators are examined separately to determine the percentage of individuals with a specific chronic mental disease identified by each morbidity indicator.

3.2.4 Step 4: Calculation mean financial result subgroups

The dataset allows to calculate the mean financial result for subgroups with specific mental diseases by using the formula below. $\hat{Y}_i$ is the predicted value from the OLS regression for individual i and Y_i is the individuals actual spending. $i \epsilon g$ indicates the individuals in group g of concern, and n_g the number of consumers in group g (Layton et al., 2018).

$$Mean\ financial\ result_g = \frac{\sum_{i \epsilon g}(\hat{Y}_i - Y_i)}{n_g} \qquad (3)$$

A positive mean financial result, when the expected costs are higher than the actual costs, indicates a predictable profit and therefore overcompensation. A negative result indicates a predictable loss and undercompensation, which again incentivizes insurers for risk selection. The mean financial result is calculated for: 1) subgroups with a specific chronic mental disease, 2) subgroups with a specific chronic mental disease that are identified by DCG, PCG and/or MYHC and 3) subgroups with a specific chronic mental disease that are ***not*** identified by DCG, PCG and/or MYHC. These last two calculations enable to answer the second and third sub question about the extent to which the RE model for mental care compensates insurers for the expected spending of individuals with specific mental diseases that are and are not identified by the morbidity indicators in the model.

Additionally, a relative measure is used to calculate the extent to which the RE model for mental care (model m) compensates for the mean financial result for subgroup g that would have occurred without risk adjustment:

$$Relative\ measure\ equalization\ effect_g = \left(1 - \frac{mean\ financial\ result\ subgroup\ g\ with\ model\ m}{mean\ financial\ result\ subgroup\ g\ without\ RE}\right) * 100\% \qquad (4)$$

3.2.5 Step 5: Sensitivity analysis

Lastly, a sensitivity analysis is performed to compare the actual predicted mental health spending according to the RE model 2025 to the predicted spending generated by the OLS regression used in this study. The sensitivity analysis also makes a distinction between the mean financial result of subgroups that are and are not picked up by the morbidity indicators. The actual predicted mental health spending according to the RE model 2025 was included as a variable in the dataset by the thesis supervisor. The aim of the sensitivity analysis is to evaluate how closely the values of predicted spending generated by this study align with the actual values defined in the RE model for mental care.

Together, these steps allow to measure the performance of the morbidity indicators in the RE model for mental care for subgroups with specific mental diseases, thereby formulating an answer to the research question.

3.3 Validity & reliability

To guarantee validity in quantitative research, it is important to have a comprehensive data coverage and minimization of selection bias (Heale & Twycross, 2015). The used dataset covers a wide range of variables from almost 1.2 million Dutch citizens. This data is drawn from nationwide registries, which reduces selection bias. Moreover, GP patient records in the Netherlands are expected to give a very complete overview of an individual's health status according to van Kleef et al. (2020). To enhance representativeness, a weighting factor is applied, as explained in paragraph 3.1. Moreover, the risk adjuster *seasonal workers* is excluded from the dataset. Hence, the results of this research are representative for the entire Dutch population, minus non-residents.

A limitation on the methodology of this study is the use of an OLS regression instead of a restricted least-squares regression. However, in the dataset a variable is included about the actual predicted spending according to the RE model of 2025 for mental care. By comparing this to the predicted spending generated by this study, a sensitivity analysis can be conducted as explained in section 3.2.5.

Furthermore, external validity is about being able to generalize findings to an external environment (Heale & Twycross, 2015). The use of a large sample strengthens the assurance of external validity. Therefore, findings may be generalizable to other countries with similar healthcare systems. However, it should be noted that the effectiveness of the Dutch RE model

may not necessarily translate to other contexts, given potential differences in factors such as population characteristics and the design of RE models.

Another measure of quality in a quantitative study is reliability (Heale & Twycross, 2015). The use of official and verified data sources contributes to a reliable study. Data from the Dutch Ministry of Health is derived from official records and therefore these sources are highly reliable and free from self-reporting biases. All analyses are conducted within a secured environment provided by CBS. The used datafile consists of a pseudonymized key, which ensures that the results obtained cannot be traced back to individuals.

4. Results

In this chapter, the findings of this study are presented. The data analysis consisted of five different steps and the results in this section are presented according to these steps. First, the results of simulating the RE model for mental care are presented. Second, the relevant subgroups are identified and then the contribution of the morbidity indicators in the model to identifying these subgroups is discussed. Also, the over- and undercompensation for subgroups with specific chronic mental diseases is calculated. In the last section a sensitivity analysis is conducted.

4.1 Step 1: Simulation risk equalization model for mental care 2025

The first step of the data analysis consisted of simulating the RE model for mental care of 2025. By performing an OLS regression with mental health spending in 2022 as the dependent variable and the risk adjusters of the RE model 2025 for mental care as the independent variables, individual mental care spending was predicted. In table 5 the R^2 and the CPM of the simulated RE model are presented. The R^2 indicates that 25.7% of the variance in mental health spending is explained by the risk adjusters in the model. The CPM shows that 30.2% of individual-level absolute differences is explained by the simulated RE model. Furthermore, the weighted mean predicted individual mental care spending ($\widehat{Y}_i$) is equal to the weighted mean actual individual mental care spending (Y_i), which is a property of the OLS method.

Table 5. Simulation RE model 2025.

R-squared	0.257
Cummings Prediction Measure (CPM)	0.302
Mean predicted individual mental care spending ($\widehat{Y}_i$)	€344.04
Mean actual individual mental care spending (Y_i)	€344.04

Note. RE=risk equalization. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset.

4.2 Step 2: Identification of relevant subgroups

The dataset contains five chronic mental diseases and a subgroup that identifies individuals with at least one chronic mental disease. These subgroups are listed in table 6, including their prevalence in the Health Insurance Act population of 18 years and older and their mean actual individual mental care spending. 3.6% of the Health Insurance Act population is diagnosed with at least one of the five chronic mental diseases included in the dataset. A

personality/character disorder is most prevalent in the population with 1.7% and a functional limitation/disability due to mental illness is the least prevalent with only 0.1%. Moreover, table 6 shows that the subgroup with senile dementia/Alzheimer's has the lowest mean actual individual spending (€212). The subgroup with schizophrenia has the highest mean individual-level spending (€8791). This indicates that the mean actual spending of these subgroups differs substantially from the overall mean mental care spending of €344.04 as listed in the previous paragraph.

Table 6. Subgroups with specific chronic mental diseases.

	Prevalence	**Mean actual individual mental care spending (Y_i)**
At least one chronic mental disease	3.6%	€2270
Functional limitation/disability due to mental illness	0.1%	€862
Senile dementia/Alzheimer's	0.8%	€212
Schizophrenia	0.3%	€8791
Personality/character disorder	1.7%	€2725
Mental retardation/intellectual disability	0.7%	€1142

Note. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset.

4.3 Step 3: Examining the contribution of the morbidity indicators

In this third step, the percentage of individuals with a specific chronic mental disease that is identified by DCG, PCG and/or MYHC is calculated. Additionally, each morbidity indicator is examined individually to assess the percentage of individuals with a chronic mental disease that it identifies. The results of these calculations are shown in table 7.

Table 7 illustrates that 44.2% of the individuals with at least one chronic mental disease in the dataset is picked up by the morbidity indicators in the RE model for mental care. Furthermore, it appears that schizophrenia is most accurately identified by the morbidity indicators in the RE model for mental care, both separately and together. From all individuals in the dataset with schizophrenia, 81.4% of them is picked up by DCG, PCG and/or MYHC. Individuals with senile dementia/Alzheimer's disease are the least accurately identified by the morbidity indicators in the RE model for mental care. Together, the morbidity indicators identify only 21.7% of the individuals with senile dementia/Alzheimer's. DCG has the smallest contribution with 9.4%. Among the other subgroups, individuals with a personality/character disorder are identified by DCG, PCG and/or MYHC in 57.3% of the cases, those with functional limitations or disabilities due to mental illness in 34.0%, and

those with mental retardation/intellectual disabilities in 28.4%. When examining the morbidity indicators separately, MYHC contributes most consistently to the identification of individuals with chronic mental diseases.

In sum, the morbidity indicators have the largest contribution to identifying individuals with schizophrenia. All other chronic mental diseases in the dataset are less consistently picked up, especially by DCG and PCG alone. MYHC generally provides the most important contribution to identifying chronic mental diseases compared to DCG and PCG individually.

Table 7. Percentage of individuals picked up by the morbidity indicators in the RE model for mental care.

	Picked up by DCG, PCG and/or MYHC	**Picked up by DCG**	**Picked up by PCG**	**Picked up by MYHC**
At least one chronic mental disease	44.2%	27.5%	23.0%	36.2%
Functional limitation/disability due to mental illness	34.0%	18.2%	16.8%	26.5%
Senile dementia/Alzheimer's	21.7%	9.4%	10.9%	14.0%
Schizophrenia	81.4%	66.0%	64.7%	70.6%
Personality/character disorder	57.3%	36.2%	26.3%	49.1%
Mental retardation/intellectual disability	28.4%	15.3%	14.7%	21.4%

Note. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset. DCG=diagnose-based cost groups, PCG=pharmacy-based cost groups and MYHC=multiple-year high-costs groups.

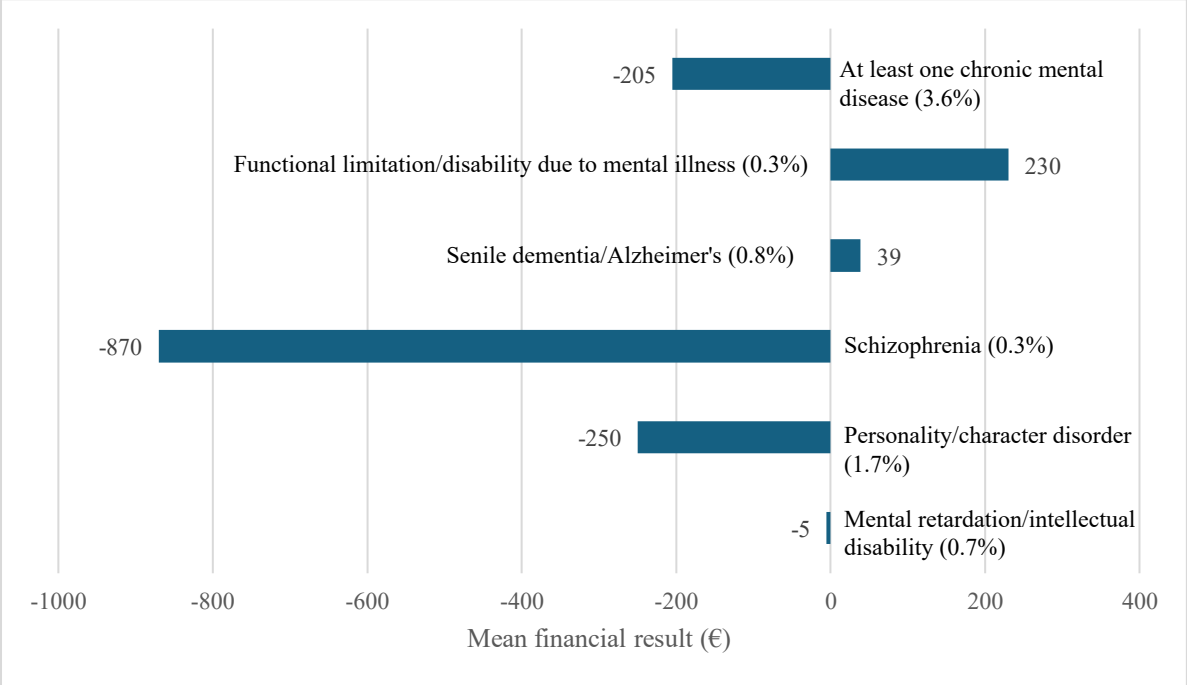
4.4 Step 4: Calculation financial result subgroups

For the fourth step of the data analysis, the mean financial result for subgroups with a chronic mental disease is calculated, indicating the over- or undercompensation for these subgroups per person per year. This step consists of different parts. First, the mean financial result is calculated for all subgroups with a specific chronic mental disease.

Figure 4 shows that the subgroup with at least one chronic mental disease has a negative mean financial result (-€205), indicating an undercompensation. The same applies to the subgroup with a personality/character disorder with an undercompensation of €250. Especially, the subgroup with schizophrenia is severely undercompensated with an amount of €870. Also, the subgroup with mental retardation/intellectual disability faces a minor undercompensation (€5). Contrarily, subgroups with senile dementia/Alzheimer's and

subgroups with a functional limitation/disability due to mental illness, are overcompensated within this RE model. The latter subgroup is overcompensated with €230 per person per year. Additionally, the weighted prevalence of individuals within a specific subgroup is illustrated in figure 4 as a percentage of the Health Insurance Act of 18 years and older.

Figure 4. Mean financial result for subgroups with a chronic mental disease.



Note. The mean financial result per individual is calculated as the mean predicted spending per person per year minus the mean actual spending per person per year. Figure relates to the Health Insurance Act population of 18 years and older in the weighted dataset. The prevalence of the subgroups is shown between the brackets as a percentage of the Health Insurance Act population of 18 years and older.

Second, the mean financial result is calculated separately for subgroups with a chronic mental disease that are identified by the morbidity indicators – DCG, PCG and/or MYHC – and for those that are ***not*** identified by these indicators in the RE model for mental care. These analyses enable to examine to what extent the over- or undercompensation of subgroups is caused by whether the subgroup is identified by the morbidity indicators in the model. The results are visible in table 8. The table also includes the part of each subgroup that is identified by the morbidity indicators, as well as the part that is not, as a percentage of the Health Insurance Act population. Additionally, the mean actual spending per subgroup is illustrated. See appendices A and B for the mean financial results for (un)identification by each morbidity indicator separately.

Table 8 shows that for every subgroup the mean actual spending is higher for the part of the subgroup that is identified than for the part that remains unidentified by the morbidity

indicators. The subgroup with at least one chronic mental disease faces an undercompensation of €187 when identified by the morbidity indicators in the model, and of €220 when not identified by the morbidity indicators. This indicates that the undercompensation for this subgroup (€205), as presented in figure 4, is caused by both the individuals that are and are not picked up by the morbidity indicators in the model. The percentage of identified and unidentified individuals is evenly distributed. When the subgroup with a functional limitation/disability due to mental illness is correctly identified by the morbidity indicators, it faces an overcompensation of €928. When not identified, the subgroup faces a substantial undercompensation (€130). The overall undercompensation of €230 for this subgroup in figure 4 suggests that the positive financial outcomes for identified individuals outweigh the undercompensation experienced by those missed by the morbidity indicators. However, the bigger part is not identified by the morbidity indicators in the model.

The subgroup with senile dementia/Alzheimer's is overcompensated with €823 when identified by the morbidity indicators. In contrast, when not identified, it faces an undercompensation of €130. The small positive result for this subgroup in figure 4 indicates that both the part that is identified and the part that is not, contribute to the minor overcompensation for this subgroup. For this subgroup also applies that the greater part is not identified by the morbidity indicators in the model. The subgroup with schizophrenia faces an undercompensation, even when identified by the morbidity indicators (€717). However, the undercompensation becomes significantly larger when the subgroup is not captured by the morbidity indicators (€1538). Nonetheless, most individuals with schizophrenia are identified by the morbidity indicators. For the subgroup with a personality/character disorder, both the part that is identified (-€310) and the part that remains unidentified (-€169), face an undercompensation. Notably is that the undercompensation is larger when individuals are identified. The mean actual spending is significantly higher for the identified part of this subgroup (€4536) compared to the unidentified part (€298). As a result, the difference between the predicted and the actual spending – i.e., the undercompensation – is larger for the part of the subgroup that is identified by the morbidity indicators.

Lastly, the subgroup with mental retardation/intellectual disability faces a large difference in compensation depending on whether it is identified by the morbidity indicators. When the subgroup is identified it is overcompensated with €500 per person per year, but when not identified it faces an undercompensation of €205. The small negative result in figure 4 (-€5) suggests that although some individuals in this subgroup are well-compensated, many are still missed.

The findings above show that there is significant variation in mean financial results for subgroups with a chronic mental disease, depending on whether they are identified by the morbidity indicators in the RE model for mental care – DCG, PCG and/or MYHC. In general, the parts of subgroups that are picked up by the morbidity indicators tend to receive more adequate compensation, while the parts that are not picked up consistently experience undercompensation. However, the subgroups with schizophrenia and a personality/character disorder still face notable undercompensation when they are identified by the morbidity indicators.

Table 8. Mean financial result for subgroups with a chronic mental disease (not) picked up by DCG, PCG and/or MYHC.

	Picked up by DCG, PCG and/or MYHC			***Not* picked up by DCG, PCG and/or MYHC**		
	Prevalence	**Mean actual spending**	**Mean financial result**	**Prevalence**	**Mean actual spending**	**Mean financial result**
At least one chronic mental disease	1.6%	€4870	-€187	2.0%	€211	-€220
Functional limitation/disability due to mental illness	0.0%*	€2344	€928	0.1%	€98	-€130
Senile dementia/Alzheimer's	0.2%	€709	€823	0.7%	€74	-€178
Schizophrenia	0.3%	€10434	-€717	0.1%	€1600	-€1538
Personality/character disorder	1.0%	€4536	-€310	0.7%	€298	-€169
Mental retardation/intellectual disability	0.2%	€3750	€500	0.5%	€106	-€205

Note. The mean financial result per individual is calculated as the mean predicted spending per person per year minus the mean actual spending per person per year. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset. The proportion of the subgroups is shown as a percentage of the Health Insurance Act population of 18 years and older. DCG=diagnose-based cost groups, PCG=pharmacy-based cost groups and MYHC=multiple-year high-costs groups.
**0.04%.*

Additionally, a relative measure was used to calculate the extent to which the RE model for mental care (model *m*) compensates for the mean financial result of subgroup *g* that would have occurred without risk adjustment. Table 9 compares the mean financial result without risk adjustment to the mean financial result with risk adjustment. It also shows the decrease in financial result caused by applying risk adjustment.

The RE model for mental care substantially compensates for all chronic mental diseases in the dataset. For the subgroup with at least one chronic mental disease, the RE model reduces the mean financial result with 76.2% and for the separate chronic mental diseases the decrease in mean financial result is even higher. The most significant

improvements occur for the subgroups with schizophrenia (90.1%), a personality/character disorder (90.8%) and mental retardation/intellectual disability (99.6%). However, some conditions still result in a financial loss for insurers despite this risk adjustment.

Table 9. Relative measure performance RE model.

	Mean financial result without RE	**Mean financial result with RE**	**Decrease in financial result with RE compared to without RE**
At least one chronic mental disease	-€862	-€205	76.2%
Functional limitation/disability due to mental illness	-€2270	€230	89.9%
Senile dementia/Alzheimer's	-€212	€39	81.7%
Schizophrenia	-€8791	-€870	90.1%
Personality/character disorder	-€2725	-€250	90.8%
Mental retardation/intellectual disability	-€1142	-€5	99.6%

Note. RE = risk equalization. The relative measures are calculated with formula 4. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset.

4.5 Step 5: Sensitivity analysis

Lastly, a sensitivity analysis was conducted to evaluate the extent to which the results generated by this study approach the actual values defined in the RE model for mental care. Table 10 illustrates the mean financial result without RE, the mean financial result with RE generated by this study and the mean financial result with RE according to the actual RE model 2025. Table 11, similar to table 8, makes a distinction between the parts of subgroups that are and are not identified by the morbidity indicators (DCG, PCG and/or MYHC), and compares the mean financial result of this study with that of the RE model 2025.

Both table 10 and table 11 show strong alignment for the conditions schizophrenia and personality/character disorders, where the mean financial result generated by this study is close to the actual mean financial result generated by the RE model 2025, with and without identification by the morbidity indicators. However, for the subgroups with a functional limitation/disability due to mental illness and senile dementia/Alzheimer's, the overcompensation found in this study is smaller than the overcompensation generated when using the actual RE model 2025. For these subgroups applies that the mean financial result

found in this study shows undercompensation for the part that is not identified by the morbidity indicators. In contrast, the actual RE model 2025 shows a slight overcompensation. For the subgroup with mental retardation/intellectual disability a minor undercompensation was found during this study, but when using the actual model an overcompensation of €314 is generated. This difference is caused by the part of this subgroup that remains unidentified by the morbidity indicators; this study shows an undercompensation of -€205 and the actual RE model 2025 indicates an overcompensation of €182.

This suggests that this study's simulated RE model is accurate for some conditions but does not quite capture the full compensatory effect of the RE model for other conditions. In general, the undercompensation for the unidentified parts of subgroups is larger in this study than when using the actual RE model 2025. An explanation could be the use of an OLS regression instead of a restricted least-squares regression as used in the actual RE model for mental care. The use of a different regression approach has no effect on the percentage of subgroups that is identified by the morbidity indicators in the model but may have effect on the found over/undercompensation for these subgroups.

Table 10. Sensitivity analysis: mean financial result for subgroups with a chronic mental disease.

	Mean financial result without RE	**Mean financial result with RE generated by this study**	**Mean financial result with RE according actual RE model 2025**
At least one chronic mental disease	-€862	-€205	-€119
Functional limitation/disability due to mental illness	-€2270	€230	€420
Senile dementia/Alzheimer's	-€212	€39	€243
Schizophrenia	-€8791	-€870	-€867
Personality/character disorder	-€2725	-€250	-€304
Mental retardation/intellectual disability	-€1142	-€5	€314

Note. The mean financial result per individual is calculated as the mean predicted spending per person per year minus the mean actual spending per person per year. RE = risk equalization. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset.

Table 11. Sensitivity analysis: mean financial result for subgroups with a chronic mental disease (not) picked up by DCG, PCG and/or MYHC.

	Picked up by DCG, PCG and/or MYHC		***Not*** **picked up by DCG, PCG and/or MYHC**	
	Mean financial result generated by this study	**Mean financial result according actual RE model 2025**	**Mean financial result generated by this study**	**Mean financial result according actual RE model 2025**
At least one chronic mental disease	-€187	-€202	-€220	-€53
Functional limitation/disability due to mental illness	€928	€997	-€130	€122
Senile dementia/Alzheimer's	€823	€1075	-€178	€12
Schizophrenia	-€717	-€733	-€1538	-€1451
Personality/character disorder	-€310	-€402	-€169	-€172
Mental retardation/intellectual disability	€500	€646	-€205	€182

Note. The mean financial result per individual is calculated as the mean predicted spending per person per year minus the mean actual spending per person per year. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset. DCG=diagnose-based cost groups, PCG=pharmacy-based cost groups and MYHC=multiple-year high-costs groups.

5. Discussion

This chapter begins by formulating an answer to the sub questions of this paper. This includes the contribution of this paper to the existing literature and the similarities and differences found in the literature compared to the results of this study. Additionally, strengths and limitations of this study, recommendations for further research and policy implications are discussed. Lastly, this chapter ends with a conclusion to the research question of this paper.

5.1 Answers to the sub questions

The first sub question addressed in this study is: *to what extent do the morbidity indicators DCG, PCG and MYHC in the RE model for mental care identify individuals with specific chronic mental diseases?* In chapter 4.3 the contribution of the morbidity indicators in the RE model for mental care to the identification of chronic mental diseases is examined. It can be concluded that the three morbidity indicators have the largest contribution to identifying the subgroup with schizophrenia (81.4%). The other chronic mental diseases in the dataset are less consistently identified by the morbidity indicators in the model. Especially the contribution of the morbidity indicators to identifying the subgroup with senile dementia/Alzheimer's is smaller than for the other chronic mental diseases (21.7%). When comparing the morbidity indicators individually, MYHC has a larger contribution to identifying the chronic mental diseases than DCG and PCG. A possible explanation for the differences in identification between the subgroups is that schizophrenia is included in the DCGs for mental care (Ministerie van VWS, 2024c). However, personality disorders are also included, yet are they only identified through DCGs in 36.2% of cases. PCGs do not include any of the specific chronic mental diseases of this study, which could be an explanation for the smaller contribution of this morbidity indicator to identifying these diseases (Ministerie van VWS, 2024d). The larger contribution of MYHCs may be explained by the assumption that individuals with multiple-year high-costs are likely to suffer from a chronic condition (Withagen-Koster et al., 2018). All subgroups used in this research are labelled as chronic in the Nivel-PCD dataset, indicating high spending for multiple years.

The second sub question that is examined in this study is: *to what extent does the risk equalization model for mental care compensate insurers for the expected spending of individuals with specific chronic mental diseases who are identified by DCG, PCG and/or MYHC?* The results discussed in chapter 4.4 provide information about the mean financial

results for subgroups with specific chronic mental diseases when they are identified by the morbidity indicators in the RE model for mental care. Table 8 shows that the part of the subgroup with a functional limitation/disability due to mental illness that is identified by the morbidity indicators faces a substantial overcompensation (€928). The same applies for the subgroups with senile dementia/Alzheimer's (€823) and mental retardation/intellectual disability (€500). In contrast, the subgroup with schizophrenia faces an undercompensation when identified (€717), just as the subgroup with a personality/character disorder (€310). These results indicate that some chronic mental diseases face substantial overcompensation when identified by the morbidity indicators in the RE model for mental care, while others are undercompensated within this model.

This second sub question is related to the third sub question of this paper, which is: *to what extent does the risk equalization model for mental care compensate for the expected spending of individuals with specific chronic mental diseases who are **not** identified by DCG, PCG and/or MYHC?* Chapter 4.4 also provides information on the parts of subgroups with chronic mental diseases that are not identified by the morbidity indicators in the RE model for mental care. For all five chronic mental diseases in the dataset applies that when they are not identified by DCG, PCG and/or MYHC, they face substantial undercompensation. Especially, schizophrenia stands out with an undercompensation of €1538 per person per year. These findings illustrate that the parts of the subgroups that are identified by the morbidity indicators tend to receive more adequate compensation, while those that are not identified consistently experience undercompensation.

When comparing these results to the mean financial results of the subgroups in figure 4, it can be concluded that both the identified parts and the unidentified parts contribute to the overall mean financial result for these subgroups. However, there is a lot of variation in mean financial results for subgroups with specific chronic mental diseases, also depending on the proportion that is identified by the morbidity indicators. Notable is the subgroup with schizophrenia, which is best identified by the morbidity indicators in the model (81.4%) but faces the largest undercompensation. However, this undercompensation is a lot higher when individuals are not identified by the morbidity indicators. Another result worth highlighting is the subgroup with a personality/character disorder, which faces even greater undercompensation when it is identified by the morbidity indicators than when it is not. An explanation may be that the part of the subgroup that is identified through the morbidity indicators has much higher actual spending than the part that is not identified. This suggests that the morbidity indicators in the RE model are more likely to identify individuals with

more severe or complex conditions and therefore higher spending. As a result, the gap between predicted and actual spending is larger for the identified part of the subgroup, leading to greater undercompensation. Although personality/character disorders are included in the DCG classification, identification does not result in more accurate compensation. The discrepancy between identification by the morbidity indicators and the inaccurate compensation for some subgroups may be caused by the gatekeeping role of GPs in the Dutch healthcare system. GPs often have information on the health status of individuals that may not use secondary care. Since the morbidity indicators in the RE model are primarily based on information through hospital treatments and drug prescriptions, this can lead to a mismatch between signaled chronic diseases in the GP data and no or limited compensation through the RE model (Oskam et al., 2023).

Another considerable result is found for the subgroup with senile dementia/Alzheimer's, which is overcompensated within this RE model. However, the morbidity indicators have the smallest contribution to identifying this condition (21.7%). An explanation for this overcompensation could be that many individuals with dementia/Alzheimer's eventually transfer to care under the Dutch Long-Term Care Act, where they receive intensive institutional or home-based long-term care (Ministerie van VWS, 2024e). Overcompensation could arise because the RE model anticipates high mental care spending, but in practice some costs are shifted to the Long-Term Care Act during the year.

The literature on this topic remains limited. In particular, the RE model for mental care has not yet been the subject of prior empirical research. A recent study by van Kleef & van Vliet (2025) did examine chronic mental diseases; however, it did not analyze specific subgroups and identification by morbidity indicators, as is done in this study. This gap in the literature highlights the relevance of this paper, which provides new insights into how the morbidity indicators in the RE model for mental care contribute to identifying specific chronic mental diseases. Van Kleef & van Vliet (2025) conclude that the current RE model for mental care substantially undercompensates subgroups with chronic mental diseases. This study confirms this finding for subgroups with schizophrenia, personality/character disorders and mental retardation/intellectual disabilities. However, for subgroups with functional limitations/disabilities due to mental illness and senile dementia/Alzheimer's, the results of this study indicate an overcompensation.

5.2 Strengths, limitations and recommendations for further research

A major strength of this study is the use of real-world data from approximately 1.2 million Dutch citizens with a basic health insurance in 2022. The combination of this dataset with the GP morbidity data from Nivel-PCD enables the calculation of the mean financial result for specific subgroups with chronic conditions. However, in the actual RE model for mental care data from the entire Dutch Health Insurance Act population of 18 years and older is used. To deal with this limitation, a weighting factor was included to enhance representativeness. Nevertheless, a recommendation for further research is the use of data from the total Dutch Health Insurance Act population of 18 years and older instead of a sample, as is done in this study.

As discussed, another limitation of this study is the use of an OLS regression instead of a restricted least-squares regression as is applied in the actual RE model for mental care. The differences observed in the sensitivity analysis in chapter 4.5 – between the mean predicted mental care spending generated by this study and the mean actual predicted mental care spending of 2025 –are likely to be associated with the use of a different regression approach. The sensitivity analysis suggests that the simulated RE model of this study is accurate for certain chronic mental diseases but does not quite capture the full compensatory effect of the RE model for others. Moreover, the undercompensation for the unidentified parts of subgroups is somewhat larger in this study than generated with the actual RE model 2025. Therefore, a recommendation for further research is the use of a restricted least-squares regression to approach the outcomes generated by the actual RE model for mental care more closely.

Furthermore, this study focused on five specific chronic mental diseases that are defined as chronic in the Nivel-PCD dataset. For further research it could be relevant to examine other chronic mental diseases, such as depression and addiction, which are included in DCGs and/or PCGs.

5.3 Policy implications

This study finds that some chronic mental diseases are substantially undercompensated within the RE model for mental care, while others face overcompensation. The contribution of identification through the morbidity indicators – DCG, PCG and MYHC – to this over/undercompensation differs across diseases. The undercompensation found for the subgroup with schizophrenia, with and without identification by the morbidity indicators,

could result in incentives for risk selection by insurers. Attracting individuals with schizophrenia does not appear to be financially beneficial for insurers. The same applies for individuals with a personality/character disorder. This subgroup faces even a larger undercompensation when it is identified by the morbidity indicators in the model compared to no identification. This indicates that the RE model does not adequately capture the individuals within this subgroup and even the part that is identified, is not sufficiently compensated.

On the other hand, individuals with senile dementia/Alzheimer's or a functional limitation/disability due to mental illness seem to be financial attractive for insurers due to the overcompensation of these subgroups. However, individuals with senile dementia/Alzheimer's often are elderly, which is a high-risk group in terms of healthcare spending. The subgroup with a functional limitation/disability due to mental illness has an overall overcompensation but faces an undercompensation when not identified by the morbidity indicators. Moreover, only 34.0% of the individuals with this condition is identified by the morbidity indicators in the model. The subgroup with mental retardation/intellectual disability shows a similar pattern; overcompensation when identified by the morbidity indicators, undercompensation when unidentified, and only 28.4% of this subgroup is actually picked up by the morbidity indicators. Since the greater parts of these subgroups remain unidentified by the morbidity indicators, these subgroups are at risk of being undercompensated, making them more vulnerable to potential risk selection by insurers.

In sum, insurers are not very likely to attract the subgroups that are overcompensated with this RE model for mental care, because of high-risk and uncertainty around identification by the morbidity indicators in the model. However, the subgroups that are undercompensated when (un)identified by the morbidity indicators within the RE model for mental care, could potentially encourage risk selection among insurers.

The used relative measure indicates that the RE model for mental care substantially compensates for all chronic mental diseases in the dataset. However, some conditions still result in an undercompensation despite this risk adjustment, indicating further approvements of the RE model for mental care are needed. A policy implication to address the undercompensation for subgroups that are not (well) identified by the morbidity indicators could be to introduce new risk adjusters or new risk classes within the morbidity indicators that better identify chronic mental diseases. Particularly, DCG and PCG could use some improvements, as these morbidity indicators have a lower contribution to identifying chronic mental diseases than MYHC. An example to improve the morbidity indicators in the model could be to add risk classes that include GP diagnoses, as it seems that there is a mismatch

between the GP morbidity data and adequate compensation through morbidity indicators. With improving these morbidity indicators, it is important that the complexity of the RE model remains manageable (Ministerie van VWS, 2024b).

An exception is the subgroup with schizophrenia, which is identified in 81.4% of the cases but still faces a severe undercompensation. To address this, it can be considered to increase the payment weights for risk classes associated with schizophrenia. The same applies for the subgroup with a personality/character disorder, which faces undercompensation despite identification by the morbidity indicators. Furthermore, the overcompensation observed for the subgroup with senile dementia/Alzheimer's may be explained by transfers to the Long-Term Care-Act, as explained before. Although this issue needs further research, if confirmed, it could justify adjusting the payment weights in the RE model associated with this condition to improve its accuracy.

Another implication could be to (re)apply ex-post cost-compensation, which compensates the insurer based on the actual spending. However, it should be noted that ex-post cost-compensation comes with the risk of decreasing incentives for efficiency (Beekman & Van der Lee, 2022).

5.4 Conclusion

This last section provides an answer to the research question of this paper, which is: *to what extent do the morbidity indicators in the Dutch risk equalization model for mental healthcare compensate insurers for the expected spending of subgroups with specific chronic mental diseases?* In general, the morbidity indicators in the Dutch RE model for mental care identify only a relatively small portion of individuals within subgroups with specific chronic mental diseases. The parts of the subgroups that are identified by the morbidity indicators tend to receive a more adequate compensation, while the parts that are not identified consistently experience undercompensation. Since the greater parts of subgroups with specific chronic mental diseases remain unidentified by the morbidity indicators in the model, these subgroups are subject to considerable undercompensation. Among all researched subgroups, only schizophrenia shows a relatively strong contribution from the morbidity indicators to identifying individuals. However, this subgroup faces the most significant undercompensation of all.

Overall, the morbidity indicators in the RE model for mental care fail to fully capture specific chronic mental diseases, resulting in undercompensation for unidentified and some

identified parts of subgroups. More specifically, the found undercompensation for most subgroups with specific chronic mental diseases is largely driven by their non-identification through the morbidity indicators in the model. The sensitivity analysis shows similar patterns when using the actual RE model 2025. This highlights the shortcomings of the RE model for mental care – particularly its morbidity indicators – in addressing specific chronic mental diseases, emphasizing the need for further improvements.

6. References

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7. Appendices

7.1 Appendix A

Table 12. Mean financial result for subgroups with a chronic mental disease picked up by DCG, PCG and/or MYHC.

	Mean financial result picked up by DCG, PCG and/or MYHC	**Mean financial result picked up by DCG**	**Mean financial result picked up by PCG**	**Mean financial result picked up by MYHC**
At least one chronic mental disease	-€187	-€449	-€317	-€311
Functional limitation/disability due to mental illness	€928	€1403	€1146	€1007
Senile dementia/Alzheimer's	€823	€1665	€620	€1160
Schizophrenia	-€717	-€1146	-€291	-€1014
Personality/character disorder	-€310	-€558	-€547	-€402
Mental retardation/intellectual disability	€500	€728	€317	€516

Note. The mean financial result per individual is calculated as the mean predicted spending per person per year minus the mean actual spending per person per year. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset. DCG=diagnose-based cost groups, PCG=pharmacy-based cost groups and MYHC=multiple-year high-costs groups.

7.2 Appendix B

Table 13. Mean financial result for subgroups with a chronic mental disease not picked up by DCG, PCG and/or MYHC.

	Mean financial result *not* picked up by DCG, PCG and/or MYHC	**Mean financial result *not* picked up by DCG**	**Mean financial result *not* picked up by PCG**	**Mean financial result *not* picked up by MYHC**
At least one chronic mental disease	-€220	-€116	-€172	-€146
Functional limitation/disability due to mental illness	-€130	-€32	€45	-€50
Senile dementia/Alzheimer's	-€178	-€129	-€32	-€144
Schizophrenia	-€1538	-€334	-€1932	-€525
Personality/character disorder	-€169	-€75	-€144	-€103
Mental retardation/intellectual disability	-€205	-€138	-€61	-€147

Note. The mean financial result per individual is calculated as the mean predicted spending per person per year minus the mean actual spending per person per year. Table relates to the Health Insurance Act population of 18 years and older in the weighted dataset. DCG=diagnose-based cost groups, PCG=pharmacy-based cost groups and MYHC=multiple-year high-costs groups.