

ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
Master Thesis Msc. Strategy Economics

Volatility of Residual Spending after Risk Equalization:
A Modern Portfolio Theory approach to identify potential sources of Risk
Selection in Health Insurance Markets with a Risk Equalization Model.

Lyset de Groot (673606)

The Erasmus University logo, featuring the word "Erasmus" in a stylized, dark green, cursive script font.

Supervisor:	Enrico Pennings
Second assessor:	Hans Kippersluis
Version:	Final Thesis
Date:	12 Augustus 2024

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

This page is intentionally left blank.

Preface

This thesis represents the culmination of my academic journey in the field of Economics and Business Economics, specifically Strategy Economics at Erasmus University Rotterdam. The research presented is inspired by my long-standing interest in the Dutch healthcare system. This thesis is motivated by the desire to contribute to efficient, high-quality, and affordable healthcare for all citizens, now and in the future.

The interest in the Dutch healthcare system was once fueled by working at PwC Advisory, Public Sector - Team Healthcare. Thank you Anne van den Boomen & May Jansen for your initial faith in me and for introducing me to the Risk Equalization Model in early 2023. My interest in the Dutch healthcare system has further been fueled by working for the Erasmus Research Initiative: "Smarter Choices for Better Health". I would like to thank Tadjó Gigenhack for the discussions and his encouragement when I first mentioned I would like to write my Master's thesis on the Risk Equalization Model.

Moreover, I would like to express my sincere thanks to PwC Tax & Legal, Risk Modelling Services, for helping me shape ideas and facilitating contact with the Ministry of Public Health, Wellbeing and Sport (VWS) to gain access to the database. A very special thanks goes out to my dear colleague, Michel Oskam. In particular for his unrivaled enthusiasm regarding the topic which kept me motivated during the challenging times. Besides, I would like to thank you for your insightful comments and suggestions.

Lastly, I would like to express my gratitude to my academic supervisor, Enrico Pennings. I greatly enjoyed your teaching in the Economics of Strategy course and was thrilled to learn that you would be my supervisor. Throughout the process, you provided invaluable guidance, encouraging me to think independently and persevere when I did not fully grasp the material (yet). Most importantly, your insightful feedback was instrumental in shaping this thesis from start to finish.

Conducting this research has been both a challenging and rewarding experience. The Dutch healthcare system is an important pillar of our society we must cherish. Therefore, I am proud I got to dedicate my time and effort to research contributing to this domain. I hope that the findings will contribute to the advancement of knowledge in the Risk Equalization Model and that the healthcare system may be as efficient, affordable, and of high quality as possible for all citizens.

Lena Trijntje Elisabeth de Groot
Rotterdam, August 2024

This page is intentionally left blank.

Abstract

The Dutch Risk Equalization (RE) system is regarded as one of the most sophisticated systems in the world of its kind. Its goal is to eliminate the incentive for insurers to select their portfolio based on underlying health indicators of individuals. Ensuring that all individuals are financially equally attractive to health insurers. The RE system aims to achieve this through an Econometric Ordinary Least Squares (OLS) model that compensates insurers with higher predicted medical expenditures more than those with lower predicted expenditures, creating a theoretically level playing field. Traditional evaluations of RE assume that equalized expected returns imply the absence of selection incentives. This thesis challenges this assumption by applying Modern Portfolio Theory (MPT) to evaluate the cost of the risk borne through volatilities of the variance of residual spending in different subgroups of insured individuals.

The variance of residual spending differs across risk classes within the RE model (heteroscedasticity of residual spending), such as the risk class concerning individuals with kidney diseases compared to a healthier population. This analysis demonstrates that when health insurers are risk averse, selection incentives persist due to the heteroscedasticity of residual spending. Using MPT, risk premiums theoretically required to compensate insurers for this financial risk are calculated, revealing substantial premiums for risk classes with high residual spending variances. This indicates that without addressing the variance in residual spending, insurers will face incentives for risk selection irrespective of an overall equalized return. Finally, this thesis suggests that policy measures, such as ex-ante risk premia, are necessary to compensate for the variance in residual spending across groups in order to further enhance efficiency and quality of care.

Keywords: Health insurance, Risk equalization, Risk selection, Risk adjustment, Residual Spending, Equalization Result, Modern Portfolio Theory, Risk Premium.

List of Acronyms:

CARA	Constant Absolute Risk Aversion
CR	Constrained Regression
CRRA	Constant Relative Risk Aversion
DCGs	Diagnosis-based costs groups
DDD	Defined Daily Dose
ESHPM	Erasmus School of Health Policy & Management
HHS	Household size
HIA	Health Insurance Act
HSM	Historical somatic morbidity
IPB	Indication of pregnancy / birth
Ministry of VWS	Ministry of Public Health, Wellbeing and Sport
MPA	Macro Performance Amount
MPT	Modern Portfolio Theory
MYHCs	Multiple-year high-cost groups
MYPC	Multi-year pharmacy costs
NZa	Dutch Health Authority
OLS	Ordinary Least Squares
PCGs	Pharmacy-based cost groups
PDCGs	Physiotherapy diagnosis costs groups
PSHCGs	Prior spending on home-care groups
RE	Risk Equalization
SES	Socioeconomic status
SoI	Source of Income
UC	Undercompensation

Contents

1	Introduction	1
1.1	Background	1
1.1.1	Health Insurance Act 2006	1
1.1.2	Risk selection	2
1.1.3	Consequences of risk selection	3
1.2	Risk equalization model	3
1.3	Readers guide	5
2	Literature	6
2.1	Evolution of the risk equalization model	6
2.2	Unpriced risk heterogeneity in the risk equalization model	7
2.2.1	Under and overcompensation	7
2.3	Findings of heterogeneity of residual spending after risk equalization	8
2.3.1	Potential solutions to mitigate the selection incentives that arise as a consequence of residual spending heteroscedasticity	8
2.4	Research gap	9
2.4.1	Research question and hypotheses	11
3	Theoretical Framework	13
3.1	Modern Portfolio Theory	13
3.1.1	Utility	13
3.1.2	Risk aversion	14
3.2	Application to the health insurance market	14
3.2.1	Risk aversion in the Dutch health insurance market	15
3.2.2	Utility functions in the health insurance market	16
4	Data	19
4.1	Data description	19
4.1.1	Risk adjusters and risk classes	19
4.2	Data preparation	22
4.3	Descriptive statistics	23
4.3.1	Descriptive statistics on sample level	23

5	Methodology	25
5.1	Estimation of the risk equalization model	25
5.2	Analysis of the distribution of residual spending	26
6	Results	28
6.1	Replication of the risk equalization model	28
6.2	Distribution of residual spending for people that are undercompensated vs. people that are overcompensated	28
6.3	Distribution of residual spending for a specific risk class	29
6.3.1	Residual spending for pharmaceutical indication of kidney diseases	30
6.3.2	Consistency of residual spending for pharmaceutical indication of kidney diseases over time	32
6.3.3	Underlying characteristics driving residual spending within kidney diseases	32
6.4	Risk premia required to compensate financial risk as a consequence of heteroscedasticity of residual spending	35
6.4.1	Risk premium required for individuals with a pharmaceutical indication of kidney disease	35
6.4.2	Risk premium required for all risk classes	36
7	Discussion and conclusion	38
7.1	Discussion	38
7.1.1	Robustness	39
7.1.2	Implications	39
7.1.3	Limitations	39
7.1.4	Recommendations for future research	40
7.2	Conclusion	41
	References	42
	Appendixes	48
	Appendix A: Simplified example of compensation on an individual level	48
	Appendix B: The number of risk adjusters & risk classes 2021-2023	49
	Appendix C: Profit margins of Dutch health insurers 2012-2022	50
	Appendix D: Descriptive statistics of residual spending	51
	Age*Gender	51
	PCGs	52
	DCGs	53
	DMECG	54
	SoI*Age	54
	Region	55
	SES*Age	56
	HHS*Age	56
	MYHC	57
	PDCG	57

PSHC	57
HSM	58
MYPC	58
IPB	58
Appendix E: Risk premia required for all risk classes in 2023 (absolute standard deviations)	59
Appendix F: Risk premia required for all risk classes in 2023 (adjusted standard deviations)	63

Chapter 1. Introduction

1.1 Background

1.1.1 Health Insurance Act 2006

In 2006 the Health Insurance Act (HIA) was introduced in the Netherlands (van Kleef et al., 2018). The main goal of the HIA is to establish a healthcare system in which access to healthcare for all is guaranteed while simultaneously maintaining high quality and efficiency of care. The HIA rests upon a solidarity, equality, and quality principle (Zorginstituut Nederland, n.d.). Through a combination of these three principles, the healthcare system is designed to have regulated competition among health insurers and among healthcare providers with the goal of providing citizens with the best quality of care at the best price. The solidarity principle states that all individuals living or working in the Netherlands are obliged to obtain basic healthcare insurance (Zorginstituut Nederland, n.d.). Consequently, all insured persons together contribute to the total costs of all curative care through premiums and taxes. The equality principle states that health insurers must accept all individuals without premium differentiation based on the individuals' health condition, age, or background. The quality principle states that health insurers have a duty of care and must guarantee basic healthcare for all their policyholders (Zorginstituut Nederland, n.d.). Moreover, the quality principle states that individuals, health insurers, and healthcare providers all have a responsibility to drive the quality of healthcare (Zorginstituut Nederland, n.d.). Therefore, individuals can change their health insurance each end of the year, to choose the insurer with the best price/quality ratio. Consequently, health insurers contract healthcare providers based on quality and efficiency (Folland et al., 2012).

In 2023, the total healthcare expenditure under the Health Insurance Act is estimated at €54.8 billion (Zorginstituut Nederland, 2024c). This expenditure is funded for 50% through nominal premiums paid by all residents older than 18 (with allowances available for those below a certain income threshold), and deductible payments¹ (van Kleef et al., 2018). The remaining 50% of the expenditure is paid by government subsidies and income-related taxes paid by both employees and employers. These contributions are consolidated into the 'Health Insurance Fund' and distributed to insurers through the Risk Equalization (RE) model. Under this system, insurers must pay a contribution for enrollees whose anticipated expenditures are below the average yearly nominal premium² and receive a contribution for those whose predicted spending exceeds the average yearly nominal premium. The major financial flows in the funding of the HIA are illustrated in figure 1.1 (van Kleef et al., 2018).

¹Deductible payments are the amounts individuals must spend before receiving coverage from their insurer (in Dutch: eigen risico).

²Average nominal premium in 2023 amount to €1650 (Rijksoverheid, 2024).

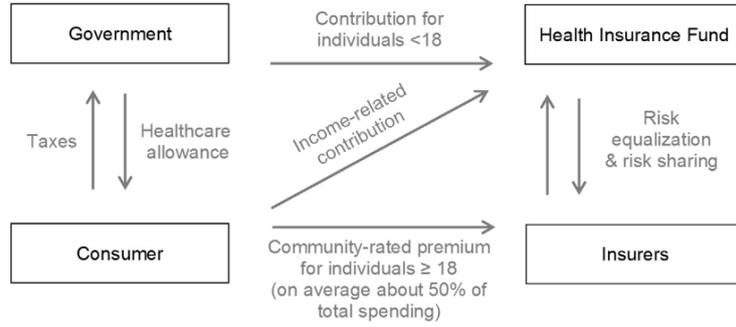


Figure 1.1: Funding of the Health Insurance Act (van Kleef et al., 2018).

The contents of basic healthcare are mandated by the government (Zorginstituut Nederland, n.d.). Basic healthcare includes, among others, primary care, pharmaceutical care, inpatient and outpatient hospital care, and mental healthcare (Zorginstituut Nederland, 2024a). Compensations for all but mental healthcare are estimated using the RE model. Compensations for insurers regarding mental healthcare is estimated using a separate risk model. Therefore, this thesis does not take the mental healthcare into consideration. Instead, the focus of this is specifically on somatic healthcare, which accounts for approximately 90% of the total medical spending in the basic health insurance act (van Kleef et al., 2018).

1.1.2 Risk selection

In unregulated markets, insurers apply premium differentiation to address the expected risk with each individual. However, in a regulated competitive market with premium regulation, insurers are not allowed to adjust premiums based on underlying characteristics (van de Ven et al., 2023). The implementation of the HIA in the Netherlands requires health insurers to accept all individuals and prohibits the insurers from using premium differentiation based on personal characteristics (NZa, 2019). Therefore, premium regulation ensures that insurers cannot charge higher premiums to high-risk individuals, thereby theoretically promoting equity and affordability (van Kleef et al., 2018).

Consequently, insurers encounter predictable profits and losses based on specific characteristics of the insured. Therefore, insurers with a relatively high proportion of high-risk individuals would be at a disadvantage compared to competitors with a relatively high portion of low-risk individuals. This is known as unpriced risk heterogeneity. Unpriced risk heterogeneity refers to predictable variation in healthcare spending between risk groups not accounted for in premiums or RE payments (Withagen-Koster et al., 2018). This leads to a financial incentive for insurers to target relatively low-risk subgroups whilst trying to dissuade enrollment of relatively high-risk subgroups (NZa, 2019). This phenomenon is referred to as risk selection. Risk selection has been defined by Newhouse (1996) and (R. C. van Kleef et al., 2013) as:

“Actions (other than premium differentiation by product) by insureds or insurers to exploit unpriced risk heterogeneity and not fully pooling the costs of low- and high-risk insureds”.

The incentive for risk selection may present in various ways. For example, insurers might design benefit packages or marketing strategies to target specific groups. Moreover, insurers are discouraged from investing in care procurement in projects for which they expect to attract individuals that make predictable losses (R. C. van Kleef et al., 2018). Consequently, risk selection can cause service-level distortion where insurers invest disproportionately into care for healthy people rather than investing in care for people with more complicated and expensive medical needs (Geruso & Layton, 2017). By not contracting the best care for individuals with certain chronic diseases, for example, the insurer can steer those individuals to refrain from that insurer. This is known as steering self-selection among individuals. Furthermore, risk selection may threaten efficiency because risk selection may be more effective in reducing the claim burden in the short run rather than promoting efficiency in care. Lastly, the incentive for risk selection is suspected to increase as price competition becomes more fierce (NZA, 2016).

1.1.3 Consequences of risk selection

Risk selection occurs when insurers target low-risk individuals and avoid high-risk individuals, undermining the goals of the RE model. This can threaten efficiency, reduce solidarity, and lower the quality of care for high-risk groups, such as the chronically ill (R. C. van Kleef et al., 2018).

Generally, offering twin products³ and targeting specific groups can be signs of risk selection (Oskam et al., 2024). Risk selection is examined through the degree of segmentation of enrollments in policies (Equalis, 2023). The Dutch Health Authority (Nederlandse Zorgautoriteit; Nza) found strong indicators of segmentation for 7 out of the 74 health insurance policies and medium indicators of segmentation for 20 out of 74 health policies (NZA, 2016). Even though these health insurance policies show indicators of segmentation, risk selection remains hard to prove (van Kleef et al., 2018; Oskam et al., 2024; NZa, 2016). This is due to difficulty distinguishing cost differences due to risk selection from cost differences due to differences in efficiency (NZA, 2016). Moreover, The absence of segmentation does not necessarily imply the absence of risk selection. When there is no systematic sorting among available plans, it could be due to an underserved market for specific characteristics, such as all insurers not offering optimal care for certain (chronic) diseases (Geruso & Layton, 2017).

In conclusion, risk selection is hard to detect, but when present its consequences severely endanger the accessibility, high-quality care, and efficiency of care (R. C. van Kleef et al., 2013, 2018). Withagen-Koster et al. (2018) argue that the mitigation of potential risk selection is a major challenge in regulated health insurance markets. Similarly, Geruso and Layton (2017) highlights selection incentives as the central issue in the competitive health insurance market.

1.2 Risk equalization model

The risk equalization (RE) model is employed as a complement to a regulated system to counter the incentive for risk selection (van de Ven et al., 2023). The goal of the system is to achieve

³Twin products are insurance products that are very similar except the pricing is different and the options to supplementary options are different. Generally, the lower-priced twin comes with less generous supplementary coverage than the higher-priced twin (Oskam et al., 2024).

the "equivalence principle". The equivalence principle aims to take away the incentive to select insureds based on underlying health indicators. Essentially, for the equivalence principle to hold, all people should be financially equally attractive to the insurer (van de Ven et al., 2023). By equalizing the expected costs across all individuals, incentives for risk selection are eliminated (van Kleef et al., 2018). In other words, in a perfect RE system, the equivalence principle allows health insurers to be fully risk-bearing without incentive for risk selection or affecting the level playing field, while preserving the incentives to control costs, in theory (van Kleef et al., 2018).

The equivalence principle is defined as the concept that goal-A is equivalent to "removing the predictable over- and undercompensations of subgroups of insured," or, alternatively, "achieving a level playing field for each risk composition of an insurer's portfolio," or, equivalently, "eliminating incentives for risk selection."

The RE model ensures that health insurers with portfolios of individuals with higher predicted medical expenditure receive higher ex-ante compensations than health insurers with a predicted low-cost group of insured (van de Ven et al., 2023). This system, in theory, creates a level playing field as the expected returns from high-cost individuals are equal to the expected returns of low-cost individuals (R. C. van Kleef et al., 2018). Therefore, in theory, health insurers are able to solely focus on efficient and integrated purchasing of care (R. C. van Kleef et al., 2013).

The RE model determines the annual ex-ante financial compensation based on the predicted healthcare expenditure of individuals within the portfolio of an insurer⁴. The compensation an insurer receives is based on the average expected costs associated with specific characteristics of each individual. The specific characteristics of each individual are used as indicators to estimate the expected healthcare costs.

The RE model in 2023 uses 14 variables⁵ that are individually observed to estimate the expected healthcare costs for all individuals (Zorginstituut Nederland, 2022c). These variables are referred to as risk adjuster variables. The risk adjuster variables consist of demographic and morbidity variables. Examples of demographic characteristics are age, gender, and socioeconomic characteristics. Examples of morbidity characteristics are pharmacy costs, costs made in prior years, and diagnosis indications (Layton et al., 2016). Within risk adjuster variables are multiple risk classes. For example, the risk adjuster variable pharmacy cost group (PCG) consists of 48 risk classes, identifying different diseases based on pharmaceutical usage. In total, there are 233 risk classes among the 14 risk adjuster variables in 2023⁶. The ex-ante compensation is based on an OLS prediction model using these 233 risk classes. The risk adjusters and their risk classes will be more thoroughly discussed in the data section, specifically section 4.1.1. The OLS prediction model will be discussed in more detail in the methods section, specifically section 5.1.

⁴See appendix A for an example of how the expected healthcare expenditure per individual is calculated.

⁵The 14 risk adjuster variables: 1. Age interacted with gender (gender*age), 2. Pharmacy-based cost groups (PCGs), 3. Diagnosis-based cost groups (DCGs), 4. Durable medical equipment costs groups (DMECGs), 5. Source of income interacted with age (SoI*age), 6. Region (region), 7. Socioeconomic status interacted with age (SES*age), 8. Household size interacted with age (HHS*age), 9. Multiple-year high-cost groups (MYHCs), 10. Physiotherapy diagnosis cost groups (PDCGs), 11. Prior spending on home care (PSHCs), 12. Historical somatic morbidity groups (HSMs), 13. Multi-year pharmacy costs groups (MYPCs), 14. Indication of Pregnancy / Birth.

⁶See section 4.1.1 for a detailed explanation of each risk adjuster, see appendix B for an overview of the number of risk classes per risk adjuster for the years 2021-2023.

RE systems are used in the health insurance markets in the USA, Germany, Switzerland, Australia, and the Netherlands, among others (van Kleef et al., 2018). The Dutch RE model is regarded as one of the most sophisticated systems in the world.

Although the Dutch RE model is regarded as one of the most sophisticated RE models, heterogeneity between the existing groups of insured is pertinent (Withagen-Koster et al., 2018). There are significant under or overcompensations for specific groups in the Dutch population leading to potential incentives for risk selection⁷. The RE model is annually evaluated and refined.

1.3 Readers guide

Chapter 2 further establishes the foundation of this research by discussing prior studies, eventually leading to the identification of the research gap, and presenting the research question and hypotheses of this thesis. Following, chapter 3 introduces the Modern Portfolio Theory and utility functions in the health insurance market, providing a theoretical framework. This chapter theoretically examines the financial incentives associated with the heteroscedasticity of residual spending. Moreover, this chapter establishes a framework to quantify risk premia to mitigate risk selection incentives across various subgroups. Next, chapter 4 describes the dataset used to analyze residual spending distribution across various risk classes over time. Chapter 5 describes the methodology used to obtain the results, forming the empirical basis of the study. Consecutively, chapter 6 presents the analysis results of the distribution of residual spending, identifying within-group patterns and assessing consistency over time. Moreover, chapter 6 provides potential compensations to eliminate selection incentives due to heteroscedasticity of residual spending, which are further examined through a sensitivity analysis. Finally, chapter 7 discusses and concludes the findings of this thesis. Chapter 7 presents a comprehensive summary of the research, its implications, and suggestions for future studies.

⁷Over and undercompensations are discussed in more detail in chapter 2.

Chapter 2. Literature

2.1 Evolution of the risk equalization model

The RE model was first introduced in 1993, initially considering only age and gender as variables (van Kleef et al., 2012). Over the years, the model has become more sophisticated, incorporating various other factors to better predict healthcare costs. The evolution of the RE model has led to considerable improvements in its predictive performance, measured by group level payment fit and individual level payment fit.

The group level payment fit indicates how well the model reduces predictable losses for health insurers. van Kleef and van Vliet (2012) studied that the ex-ante Dutch RE model of 2011 reduces the predictable losses, that would have occurred without compensations, for health insurers with an average of 70%, whereas this reduction for the 1993 model only reached an average of 40% (van Kleef et al., 2012). By 2023 the model reduces the predictable losses up to 99.3% (ESHPM, 2023a). The second measure, the individual level fit, has also seen improvements in the model. To quantify the individual fit we analyze the R^2 value. The R^2 is a statistical measure that indicates the proportion of variance that is explained by the independent variables. The R^2 statistic is one of the most commonly used metrics for assessing the performance of the RE model (van de Ven et al., 2023). In 2010 the individual level fit reached a R^2 value of 25% (van Kleef et al., 2018). By 2017 this value had increased to 31% and by 2023 this value increased to 32.7%. The evolution of the predictive power on the individual level is depicted in the graph below. The CPM is another measure to evaluate the performance of the regression model.

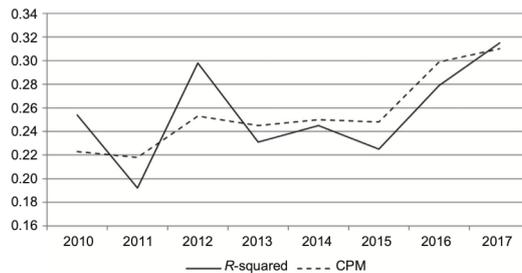


Figure 2.1: Individual level fit, predictive power (R^2) (van Kleef & van Vliet, 2012).

The substantial improvement of the RE model can be attributed to the introduction of new risk adjuster variables. These include Multiple-year High Cost Groups (MYHCGs) in 2012, Durable Medical Equipment Cost Groups (DMECGs) in 2014, Physiotherapy Diagnosis Cost Groups (PDCGs) in 2016, Prior Spending on Home Care (PSHC) in 2016, and new Pharmacy Cost Groups (PCGs) for people with rare diseases in 2017 (van Kleef et al., 2018; van Kleef & van Vliet, 2012). Which are all examples of improving the ex-ante compensation of the RE model by adding relevant risk adjusters and/or risk classes.

More recently, in 2023, a risk adjuster variable was introduced for pregnant people or people

who have given birth in that year. This risk adjuster was introduced partly in response to the study by (Douven & Mannaerts, 2008) who provided an example of service level distortion in the health insurance market leading to market segmentation. The "ZEKUR health plan" contracted relatively few hospitals making it not an attractive health plan, especially for women who are pregnant or want to get pregnant. On average, giving birth amounts to costs of €7000 (Otter, 2012). Since the RE model up till 2023 did not include a risk adjustment variable for pregnancy or childbirth, pregnant women were structurally undercompensated while non-pregnant women of the same age class, all other factors being equal, were structurally overcompensated (Douven & Mannaerts, 2008). Similarly, the risk classes have been re-adjusted for the risk adjuster Pharmaceutical Cost Groups, introducing 5 new risk classes from 2022 to 2023 to reduce predictable over and undercompensations within risk classes of this variable (ESHPM, 2023a).

An example of studies that aim to contribute by improving the prediction method is the study by van Kleef et al. (2017) who investigate the use of constrained regression to estimate ex-ante compensations. The model includes constraints that set a maximum limit on undercompensation or overcompensation at the group level. The constrained least squares regression aims to minimize the squared deviations at the individual level while imposing a maximum limit on the under or overcompensation for certain groups (van Kleef et al., 2015). Compared to the regular OLS the CR leads to a decreased R^2 at the individual level (van Kleef et al., 2023). This is because the regular OLS minimizes the squared deviation at individual level without limitations due to having certain constraints.

2.2 Unpriced risk heterogeneity in the risk equalization model

Despite advancements, the Dutch RE model still exhibits unpriced risk heterogeneity, leading to overcompensations or undercompensations within specific risk classes (Withagen-Koster et al., 2018).

To address unpriced risk heterogeneity, it is essential to understand the consequences of risk selection and identify how often and in which ways risk selection manifests. Groups experiencing undercompensation often display greater heteroscedasticity in residual spending. Identifying and addressing these groups enhances the accuracy and fairness of the RE model.

2.2.1 Under and overcompensation

In 2019, 22% of insured individuals were structurally undercompensated, with 3% being structurally undercompensated over multiple years (NZa, 2016). Individuals that are structurally undercompensated are individuals that have been undercompensated for three years or more. Undercompensation is more prevalent among individuals who score positively on morbidity indicator risk adjusters (PCG, DCG, PDCG, MYHCG, or DMECG) (van Kleef et al., 2015; Withagen-Koster et al., 2018). Subgroups prone to undercompensations include chronically ill and people with disabilities as well as the less educated (Equalis, 2023). This is confirmed by (Withagen-Koster et al., 2023) who also find that chronically ill are persistently unprofitable on average while healthy people are consequently profitable. Subgroups prone to overcompensation include, among others, students and highly educated (Equalis, 2023).

Both Withagen-Koster et al. (2018) and Oskam et al. (2024) argue that subgroups with higher somatic medical spending present more widely dispersed residual spending patterns.

As the subgroups prone to undercompensations generally present higher average healthcare costs, the groups prone to undercompensations are naturally interesting for the rest of this thesis.

2.3 Findings of heterogeneity of residual spending after risk equalization

Oskam et al. (2024) examined eight subgroups. These subgroups consist of: the entire population, individuals aged 0-64 years and 65+ years old, those with and without morbidity flags, individuals with the indication of belonging to the Pharmacy Cost Groups (PCG) of diabetes (PCG 12 - 15), individuals with certain conditions (DCG10), and those with extremely costly pharmaceutical usage (PCG38). The study found that mean spending positively correlates with the dispersion of residual spending.

Oskam et al. (2024) found a standard deviation of €6,978 for the entire population. For individuals without any morbidity flag, the standard deviation is €4,646. For people with one or more morbidity flags, the standard deviation is €11,378. It is important to note that 75% of the population belongs to the first group and 25% to the latter. Therefore both these risk groups consist of a substantial part of the population. The underlying specific risk classes drive the average standard deviation up or down. The heteroscedasticity indicates that the RE model does not completely remove unpriced risk heterogeneity, even for a broad set of morbidity-based risk adjusters (Oskam et al., 2024).

2.3.1 Potential solutions to mitigate the selection incentives that arise as a consequence of residual spending heteroscedasticity

Addressing heteroscedasticity in residual spending is crucial for eliminating incentives for risk selection. Withagen-Koster et al. (2018) recommends further improving the RE model by broadening and refining morbidity-based risk adjusters. On the other hand, Oskam et al. (2024) suggests designing premium adjustments for higher spending subgroups as a potential solution.

Oskam et al. (2024) identifies three potential solutions to mitigate the financial incentives arising from the heteroscedasticity of residual spending.

1. Outlier risk sharing:

Mitigate selection incentives by directing ex-post compensations toward individuals who are outliers in residual spending, a strategy known as outlier risk-sharing. A downside to this option is that the ex-post compensations may reduce cost-control incentives.

2. Limited premium differentiation, allowing markups across individuals:

Mitigate selection incentives by allowing limited premium differentiation. A downside to this option is that it counters the solidarity principle.

3. Modify the risk equalization payments and compensate insurers ex-ante for the heteroscedasticity in residual spending:

Mitigate selection incentives by modifying RE payments to compensate insurers for heteroscedasticity. The modified RE payments provide higher compensations for high-variance groups and lower compensations for low-variance groups. Oskam et al. (2024) provides a measure of how to modify the RE payments for highly volatile risk groups. The study continues to determine ex-ante modified RE payments using the Sharpe ratio. The Sharpe ratio is a method using risk aversion and volatility as dependent variables in determining the modification of the payments.

This thesis aims to contribute to the third solution proposed by Oskam et al. (2024) as to reduce selection incentives from heteroscedasticity of residual spending. This study investigates the modification of RE payments per existing risk class to compensate insurers ex-ante for heteroscedasticity of residual spending. The modification is in the rest of this thesis referred to as "risk premium".

Oskam et al. (2024) argues that the Sharpe ratio accounts for the risk aversion of insurers because it indicates a desired profit mark up for various investments. A higher Sharpe ratio requires a higher return, indicating that investors who require a higher Sharpe ratio are more risk-averse. Therefore, a constant Sharpe ratio gives different required returns for different volatilities. However, some potential downsides to using this method would be that the Sharpe ratio in itself is dependent on both the risk-free rate of return and the rate of return of the risk group.

The risk-free rate is theoretically the return on an investment with zero risk. In this case, the risk-free rate would most probably be the risk group consisting of healthy individuals. However, in practice, it would be hard to determine exactly what group of individuals will determine the risk-free rate. As the risk-free rate is dependent on the performance of a healthy individual group the risk-free rate would not be constant. Moreover, the risk-free rate of the healthy would in theory be equal to 0 (perfectly equalized). However, in reality, this depends on the exact risk groups that are used to compute the risk-free rate. Therefore, a constant Sharpe ratio may not be the most optimal measure to determine equalized results as it is a relative proxy between the risk-free rate and the risk group of interest.

Alternatively, in financial evaluations, government bonds are often used as the risk-free rate. However, in that case, the risk-free rate would not be constant and could fluctuate due to economic conditions, monetary policy changes, and inflation.

The next chapter introduces another financial theory, the Modern Portfolio Theory (MPT). This theory overcomes the issues as stated in the previous paragraph. Using MPT, this thesis aims to capture the risk premiums needed for different risk groups. Moreover, MPT captures risk aversion as a distinct variable enhancing its applicability in this context.

2.4 Research gap

As discussed in the introduction and the literature section it is important to eliminate incentives for risk selection. Although sophisticated, the current RE model does not yet eliminate all predictable unpriced risk heterogeneity (Withagen-Koster et al., 2018). Prior research predominantly focuses on improving the ex-ante compensation by 1) improving the model and 2)

by adding relevant risk classes and risk adjuster variables. Both improve the accuracy of estimations of the expected average healthcare costs for specific risk groups. The distribution of healthcare costs within risk classes has not been taken into account until recent research by (Oskam et al., 2024). Research in the distribution and variances of the residuals spending risk classes can further complement the understanding of unpriced risk heterogeneity. The presence of unpriced risk heterogeneity is causal for potential risk selection incentives (Withagen-Koster et al., 2018). Oskam et al. (2024) argues that perfect equalization of the mean expected result for a risk class does not guarantee the absence of selection incentives. Therefore, Oskam et al. (2024) investigates the distribution of excess spending of insurers across different groups of insured assessed on the Dutch RE model of 2021. In this research, the residual spending shows a heteroscedastic distribution of residual spending comparing old vs. young people, and healthy people vs. people with morbidity indicators (which are often indicators of chronic illnesses). Oskam et al. (2024) argues that heteroscedasticity of residual spending is a potential source of incentives for selection risk for two reasons. The first reason is because of the uncertainty of financial return. The second argument is based on the variation in solvency requirements linked to an insurer's portfolio. Moreover, Oskam et al. (2024) provides three potential solutions to mitigate the incentive to risk selection.

This thesis builds further upon the study by Oskam et al. (2024). Specifically, this thesis builds upon the argument of heteroscedasticity being the cause of incentives for risk selection because of the uncertainty of financial return. Moreover, this thesis builds upon the proposed solution of a modified ex-ante RE payment to account for variance in residual spending. This thesis aims to contribute to the recent findings of Oskam et al. (2024) in threefold.

Provide additional insights on the degree to which heteroscedasticity of residual spending is a source of potential risk selection.

Oskam et al. (2024) argues that investors are typically risk averse and prefer certainty over uncertainty. Oskam et al. (2024) necessitates further research to adequately alleviate the risk selection incentives emerging from heteroscedasticity between subgroups. Therefore this thesis builds upon the variance/expectation framework as introduced by Oskam et al. (2024).

Subsequently, this thesis uses MPT to further investigate potential preferences for insurers between risk classes taking the variance of residual spending, and the risk aversion of insurers into account. MPT is used to further quantify what risk premia would be required for insurers to be indifferent between individuals from different risk classes. Moreover, Oskam et al. (2024) argues that the risk premia would be subject to the respective size of the group of insureds per insurer. Oskam et al. (2024) therefore considers hypothetical portfolios ranging from 1,000 to 1,000,000 individuals. Contradictory, this thesis considers the risk premia that would be required on a population level for each risk class. Following, the thesis computes the risk premia per risk class per individual. MPT is used as a theoretical framework to quantify the required risk premia.

Estimate consistency of heteroscedasticity of residual spending over time.

Oskam et al. (2024) necessitates further research to adequately alleviate the risk selection incentives emerging from heteroscedasticity between subgroups. Withagen-Koster et al. (2018) emphasizes that the heteroscedasticity between groups must be predictable in order to be unpriced risk heteroscedasticity. Therefore, the differences in residual spending must be predictable to be actual sources of risk selection. Therefore, this thesis tests if the heteroscedasticity between different subgroups is consistent over time from 2021-2023.

Investigate heteroscedasticity between and within risk classes.

The study by Oskam et al. (2024) investigated eight subgroups that are relatively general⁸. Therefore, further specification of subgroups can be valuable. This thesis investigates the prevalence of heteroscedasticity for more specific risk classes. Providing an elaborate and practical overview of which risk classes are potential sources of incentives to risk selection.

Moreover, previous studies have not discussed underlying patterns within subgroups that drive the dispersed residual spending. Therefore, this thesis tries to identify what underlying characteristics drive the dispersion of residual spending within a specific risk class.

2.4.1 Research question and hypotheses

Based on the arguments put forward in the introduction and in the literature section, I define the following research question:

To what extent does the variance of residual spending of subgroups of insured contribute to an incentive for risk selection in a health insurance market?

Following, the main research question the following sub-questions emerge:

1. Under a scenario that the equivalence principle holds, meaning there is no predictable under and overcompensation between groups of insureds, if we assume health insurers to be risk averse, in what form do incentives for risk selection remain?

Hypothesis: Incentives for risk selection in the current RE model remain through differences in the variance of residual spending for subgroups of insured, subject to the degree of risk aversion of health insurers. The variance in residual spending is hypothesized to be significantly different between different groups, being a form of unpriced risk heterogeneity. Unpriced risk heterogeneity is causal to potential risk selection incentives.

2. To what extent are risk premiums required to achieve the equalization principle for different groups of insured?

Hypothesis: Assuming insurers are risk averse, health insurers require a risk premium to compensate for variance in residual spending. The required premium is dependent on the magnitude of the variance. The variance is expected to be higher for subgroups with higher

⁸The study by Oskam et al. (2024) used the following subgroups: 1. entire population, 2. individuals aged 0-64, 3. individuals 65+, 4. no morbidity flags, 5. ≥ 1 morbidity flag, 6. diabetics (PCG12-15), 7. cluster of conditions (DCG10), and, 8. extremely costly pharmaceutical usage (PCG38).

healthcare expenditures. The required risk premium is expected to be higher for groups of insured that are high healthcare consumers compared to groups that use relatively little healthcare.

3. To what extent is heteroscedasticity of residual spending attributable to underlying characteristics within the respective risk group?

Hypothesis: The distribution of residual spending in a risk class may be driven by specific underlying characteristics. Individuals with higher predicted costs in other categories are hypothesized to cause larger within-group differences in residual spending.

This thesis aims to address the questions posed above and contribute to the recent study by Oskam et al. (2024). The exact magnitude of the findings is based on the context of the specific RE system. The findings are, amongst others, subject to international regulations. The Netherlands is used as a case study in this thesis, using Dutch administrative data made available through the Ministry of VWS.

Chapter 3. Theoretical Framework

3.1 Modern Portfolio Theory

Modern Portfolio Theory (MPT), as introduced by Markowitz (1952), is an investment framework designed to optimize the expected returns of a portfolio for a given level of risk, with volatility serving as the measure of risk. In other words, portfolio holders aim to maximize utility, which is determined by the expected return of the investment, the level of risk aversion, and the investment's volatility (Bodie et al., 2014). The MPT uses a standard function:

$$U = E(r) - \frac{1}{2}\alpha\sigma^2 \quad (3.1)$$

Where the U depicts the Utility, $E(r)$ the Expected return of the investment, the α stands for the level of risk aversion of an investor and the σ represents the volatility of the investment. This function is derived from the idea that investors have preferences and value one option over another. Therefore, the MPT formula is derived from utility functions and risk levels.

3.1.1 Utility

Utility, in this context, refers to the satisfaction or benefit an investor receives from a particular investment outcome. Investors have different levels of risk aversion, which influences their utility. A utility function u represents an investor's preferences over different investment possibilities.

An investor is said to be risk-averse if their utility function satisfies the following condition for any random wealth \tilde{w} ⁹ with mean w (Back, 2017)

$$u(w) \geq E[u(\tilde{w})] \quad (3.2)$$

This means risk-averse investors prefer a certain outcome over a risky one with the same expected return. Similarly, a risk-averse investor would prefer to avoid a fair bet. Meaning, if \tilde{x} is a zero-mean random variable and w is a constant, then:

$$u(w) \geq E[u(w + \tilde{x})] \quad (3.3)$$

The difference between the utility of a sure thing and the utility of the expectation of the same thing is known as Jensen's inequality. This inequality is characterized by the concavity of the utility function (Back, 2017). The concavity of the utility function is a consequence of the exponential in the utility function (as in equation 3.6).

Portfolios with the highest expected returns for a given level of risk and portfolios with the lowest level of risk for a given expected return offer the best risk-return trade-off (Mangram, 2013). The best risk-return trade-offs are known as the investment possibilities that lie on the

⁹A tilde is used to denote a random variable.

efficient frontier. The slope of the efficient frontier depends on the degree of risk aversion. More risk-averse investors will have a steeper efficient frontier, reflecting their preference for lower levels of risk. Therefore, the degree of risk aversion plays a crucial role in portfolio construction.

3.1.2 Risk aversion

Risk aversion is a key concept in understanding behavior in decision-making situations involving uncertainty (Eeckhoudt & Schlesinger, 2013). It refers to the subjective attitude towards uncertainty and typically manifests as a preference to avoid risk (Almansour et al., 2023). The degree of risk aversion is reflected in the concavity of the utility function (Eeckhoudt & Schlesinger, 2013). In a scenario involving two assets with different degrees of risk but offering the same return—individuals, will typically find the asset with the lowest risk more attractive (Ross, 1981; Oskam et al., 2024).

Different industries display varying levels of risk aversion based on several factors, including the nature of their operations, market dynamics, regulatory environment, and historical performance (Almansour et al., 2023). The majority of financial research is based on utility functions with linear risk tolerances (Back, 2017). Utility functions with linear risk tolerances could be either concerning constant absolute risk aversion (CARA) or constant relative risk aversion (CRRA)(Back, 2017).

CARA implies that the attitude towards risk does not change with changes in wealth of the investor. Constant absolute risk aversion is defined as:

$$\alpha(w) = -\frac{u''(w)}{u'(w)} \quad (3.4)$$

CRRA implies that the attitude towards risk is proportional to initial wealth of the investor (Back, 2017).

Constant relative risk aversion is defined as:

$$p(w) = w\alpha(w) = -\frac{wu''(w)}{u'(w)} \quad (3.5)$$

The degree of risk aversion is usually thought to be fairly stable for industries as the degree of risk aversion reflects deep-rooted preferences (Gai & Vause, 2005). The degree of risk aversion in the Dutch health insurance market is further discussed in subsection 3.2.1.

3.2 Application to the health insurance market

In this thesis, I consider the health insurers market through the MPT perspective. Under this framework, insurers can be considered investors, while individuals can be considered to be investments. Insurers get compensated for each individual in their portfolio based on the expected healthcare costs of this specific individual. The different risk classes can be regarded as different portfolios for the insurer to invest in¹⁰, each risk class having its results and risks.

¹⁰Please note that insurers cannot actually invest in risk classes in such a way that they can choose which individuals to enroll and which not. Insurers must accept all who seek insurance at their services.

The actual healthcare costs are not necessarily equal to the predicted costs. The difference between what the insurers get for an individual and what they need to spend on an individual can be considered the expected return of the insurer for that specific individual. The result of the actual costs minus the RE compensations is also known as "Residual Spending". Note that when residual spending is positive the insurers need to spend more than what they received on the individual. In the case of residual spending, the insurers have a negative result. When residual spending is negative the insurers get more compensation than the costs made by an individual.

The average residual spending for any risk class can be considered the expected return of that risk class. The distribution of the residual spending within a risk class can be regarded as the volatility, i.e., the risk of the investment.

3.2.1 Risk aversion in the Dutch health insurance market

Risk neutrality of insurers is unlikely (Back, 2017; Oskam et al., 2024; Withagen-Koster et al., 2018). This can be attributed to two main reasons:

1. **Ex-Ante Equalization:**

With ex-ante equalization, the health insurer is at financial risk. Health insurers depend on the contributions through the RE model and premiums charged for the insurance, irrespective of the actual costs that will be incurred.

The financial risk that insurers bear has increased significantly over time. From 1993 to 2011, the financial risk increased from 3% to 74% (van Kleef et al., 2012). The financial risk increased even further from 2011-2016, reaching levels approximating 100% (van Kleef et al., 2018). Moreover, the incentives for risk selection are suspected to increase as the price competition becomes more fierce. Once a health insurer begins profitable risk selection, the other health insurers will not be able to stay behind for competitive reasons (Ross, 1981).

2. **Regulated Non-profit:**

The Dutch health insurers are organized from a public perspective. In the regulated non-profit insurance market insurers cannot make any profits on their patient portfolio by law. Therefore, health insurers most likely do not have a high-risk aversion level. Even though they cannot cash out any profits, health insurers aim to be slightly profit-making to set reserves to use in case of a bad year (Achmea, 2022). The insurer must comply with European regulations which state that in 199/200 years the insurer must remain solvent (European Parliament and Council of the European Union, 2009). Therefore, following the regulation set for health insurers, health insurers must be slightly risk averse. Insurers aim to make slight profits to fuel their reserves. In appendix C, the yearly profit margins of Dutch health insurers from 2012-2022 are portrayed. The average profit margin over this period is 1.047.

In conclusion, because of ex-ante compensation and because Dutch health insurers must operate under European solvency regulations risk neutrality for health insurers is unlikely.

The degree of risk aversion is generally considered to be relatively stable for different actors in the same industry, as the degree of risk aversion reflects deep-rooted preferences (Gai & Vause, 2005). However, within the health industry, differences in the degree of risk aversion are likely influenced by the size of the health insurer. Larger insurers tend to have a risk profile that closely mirrors the population mean. Therefore, the risk posed by heteroscedasticity of residual spending most likely diminishes for larger health insurers.

From a practical point of view, the introduction of a risk premium in the RE model to compensate for heteroscedasticity will most likely be a uniform risk premium for all health insurers in the Dutch health insurers market. If risk premiums were differentiated based on the specific risk aversion of each insurer (with larger insurers being less risk-averse and smaller insurers being more risk averse), this could stimulate inefficient practices, potentially leading to an incentive to increase the number of smaller health insurers.

Therefore, it is assumed that risk aversion is independent of the initial size (or wealth) of the insurer. Consequently, this thesis assumes CARA for Dutch health insurers.

According to Oskam et al. (2024), the risk aversion of Dutch health insurers is likely to be relatively low due to their public organization structure and non-profit orientation¹¹. Based on the arguments presented in this section, the CARA value should reflect that Dutch health insurers are cautious (i.e., risk-averse) but do not have an overly conservative approach to risk. Given the limited research on the precise magnitude of the CARA value, a relatively broad range is estimated, with CARA values between 0.01 and 0.10.

Note that the concavity of the utility function becomes steeper as the level of risk aversion increases. As a result, the average risk aversion in the health insurers market may lead to overestimations of the required risk premium. This should be carefully considered by the reader when interpreting required premiums over various levels of risk aversion.

3.2.2 Utility functions in the health insurance market

The RE model aims to realize perfect equalization for each risk class (van de Ven et al., 2023). This means that the model aims to ensure that for each risk class, the average residual spending equals zero. The RE model does not take the distribution of the residual spending per risk class into account. This would suggest that from a Modern Portfolio Theory perspective, health insurers are risk-averse and there is variation in residual spending between different risk classes, even if the average residual spending may be equal for all risk classes, the utility insurers get from individuals in different risk classes differs (i.e., equation 3.2 holds).

Where \tilde{x} is the result after risk equalization (i.e, residual spending) with mean x . Note that because of the OLS properties of the RE model, the mean x is zero for each risk class per definition. Consequently, equation 3.3 holds with \tilde{x} being a zero mean random variable, i.e. positive or negative residual spending.

As discussed in the previous section, I assume CARA for health insurers in the Dutch health insurance market. Following Back (2017) all CARA utility functions are a monotone

¹¹For more detail, refer to the paper: "Heteroscedasticity of residual spending after risk equalization: a potential source of selection incentives in health insurance markets with premium regulation" (Oskam et al., 2024).

affine transformation of the following negative exponential utility function:

$$U(x) \geq -e^{-\alpha x} \quad (3.6)$$

Where α is the absolute risk aversion, which is a constant given that the risk aversion among health insurers is the same. w is the wealth received by an insurer for having an individual from a certain risk class in its portfolio.

Let us assume that the residual spending (\tilde{x}) is normally distributed for all risk classes with mean x and variance σ^2 . Then the expected utility of having an individual of any risk class is equal to:

$$E[e^{\tilde{x}}] = e^{x + \frac{1}{2}\sigma^2} \quad (3.7)$$

As described before, \tilde{x} with mean x is the same as $-\alpha\tilde{\epsilon}$ with mean zero and variance $\alpha^2\sigma^2$:

$$E[e^{-\alpha\tilde{\epsilon}}] = e^{\frac{1}{2}\alpha^2\sigma^2} \quad (3.8)$$

$E[e^{-\alpha\tilde{\epsilon}}]$ is equal to $e^{\alpha\pi}$ given that we assume a normal distribution and π is the risk premium to compensate the variation $\tilde{\epsilon}$.

In other words:

$$e^{\alpha\pi} = e^{\frac{1}{2}\alpha^2\sigma^2} \quad (3.9)$$

To determine the risk premium for equal utilization of portfolios for health insurers with a constant risk aversion we determine π . The amount an insurer would be willing to pay to avoid the uncertainty associated with a specific risk class is denoted by π . The utility obtained by insurers from each risk class can then be calculated by the average expected equalization result (which is equal to the average expected residual spending (\tilde{x}) - the risk premium (π))¹².

Which implies:

$$\alpha\pi = \frac{1}{2}\alpha^2\sigma^2 \quad (3.10)$$

Consequently,

$$\pi = \frac{1}{2}\alpha\sigma^2 \quad (3.11)$$

Therefore, the required risk premium to achieve the equivalence principle can be obtained using equation 3.11. The risk premium is necessary to adhere to the equivalence principle. Without the risk premium, the utility insurers receive from different groups of insured are not equalized in the current model.

Following this, even when residual spending is equalized between risk classes (A1) the utility for insurers might still be different over different risk classes if health insurers are risk averse (A2). Let us further exemplify using a situation with two risk classes (i and j). Suppose risk class

¹²Since $U(\tilde{x} - \pi) = e^{\alpha\pi}$.

i has a larger variance than risk class j (A3). The respective utility functions for the insurers would be as follows:

$$U_i = x_i - \frac{1}{2}\alpha\sigma_i^2 \quad (3.12)$$

$$U_j = x_j - \frac{1}{2}\alpha\sigma_j^2 \quad (3.13)$$

With:

A1: $x_i = x_j$

A2: $\alpha > 0$

A3: $\sigma_i^2 > \sigma_j^2$

Then:

$$U_i < U_j \quad (3.14)$$

Consequently, subgroups with the lowest volatility¹³ maximize the utility of the portfolio holder, i.e., the insurer. Thus, even with the sophisticated RE Model, incentives for risk selection persist based on the volatility of the risk classes. In other words, more volatility in the residual spending of a risk class leads to increased incentives for risk selection. The volatility of variances can be addressed by implementing an ex-ante risk premium π .

In conclusion, health insurers are compensated for the average expected costs of each risk class in the current system. However, if health insurers are risk-averse and the variance differs significantly across risk classes, their utility will vary for different risk classes (equation 3.14). To address this, a risk premium (π) should be introduced to account for the differences in the variance of residual spending between risk classes (equation 3.11).

The next chapters will empirically investigate if differences in variances between different risk classes are significant in the RE model. In the case of significant differences, the required risk premia, subject to the CARA of health insurers, will be calculated

¹³Risk classes consisting of healthy individuals are expected to have the smallest variance.

Chapter 4. Data

4.1 Data description

This section describes the data used to study the perception of risk regarding the volatility of the costs and compensation in the Dutch RE model and to examine to what extent utilities are different across groups of insured. I use data containing individual information on somatic medical spending covered under basic health insurance and the risk characteristics for all citizens with basic health insurance for the years 2021-2023. The information on somatic medical spending is estimated using healthcare expenditure data from year $t-3$. In other words, the 2018, 2019, and 2020 healthcare expenditure datasets are prepared to estimate the compensations for 2021, 2022, and 2023 respectively.

To protect privacy, the citizens' service numbers (BSN numbers) were made anonymous by a third trusted party before the dataset was made available for this research¹⁴.

4.1.1 Risk adjusters and risk classes

The risk adjusters and the number of risk classes per adjuster change slightly over time. The dataset consists of 12 risk adjusters in 2021 and 13 risk adjusters in 2022. The dataset consists of 14 risk adjusters in 2023 that collectively account for 233 risk classes¹⁵. Risk classes take the form of dummy variables with a value of 1 (0) for individuals who are (not) members of that risk class.

In 2023, the risk adjuster IBP has been introduced as the costs of women who are pregnant are significantly higher than the healthcare costs of women who are not. Moreover, there are 5 risk classes added to the FCG risk adjuster to compensate people who do make substantial usage of specific medicines but do not reach the threshold to be classified in the corresponding FCG yet (Zorginstituut Nederland, 2020b, 2021b, 2022c). The slight alterations of the risk adjusters and risk classes do not influence the analysis of this thesis. when analyzing risk classes it is made sure there have not been fundamental changes for these specific risk classes as a consequence of the changing RE model.

The risk adjusters in 2023 (Zorginstituut Nederland, 2022b; ESHPM, 2020a, 2021, 2022; de Vries, 2022) are the following:

1. **Age interacted with gender (Gender*age):** Classification of age into 18 groups of 5 years for both men and women¹⁶. The age group 15-24 has a different classification: 15-17 and 18-24 years because individuals are considered adults from 18 years. There are two additional categories for 0-year-olds (born the prior year, and born this year) and a category for 90+ years. Total: 42 risk classes.

¹⁴According to Dutch Civil Law, Article 7:458, obtain informed consent from patients or approval from a medical ethics committee for observational studies that do not contain directly identifiable data is not mandatory.

¹⁵Please refer to appendix B for a more detailed overview of the risk adjusters and the number of risk classes for the years 2021-2023.

¹⁶In the case people are registered as unidentified gender these individuals are registered in the female risk class.

Each individual must score positive on one and only one risk class of the risk adjuster "Gender*Age". The model uses the age of the individuals on June 30th in the year prior.

- 2. Pharmacy-based cost groups (PCGs):** 47 PCGs, based on extramural dispensed pharmacy prescriptions in the year t-1. Individuals are classified in a positive PCG risk class if they have received 180 defined daily dosages¹⁷ (DDD) of a particular pharmaceutical within the last year. There is an additional risk class for insured persons not classified in any PCG. Total: 48 risk classes.

Individuals can be classified into multiple PCG risk classes simultaneously. There are restrictions on which PCGs can be combined and which cannot be combined.

- 3. Diagnosis-based cost groups (DCGs):** There are 26 DCGs based on clusters of combinations of hospital diagnoses plus diagnosis treatment combination¹⁸ (DTC) care products three years prior¹⁹. There is an additional risk class for insured persons not classified in any DCG. Total: 27 risk classes.

Individuals can be classified in multiple DCG risk classes simultaneously. There are restrictions on which DCGs can be combined and which cannot be combined.

- 4. Durable medical equipment cost groups (DMECGs):** There are 14 DMECGs based on the usage of assistive devices in the last year. Individuals can be classified into multiple DMECGs simultaneously. There is an additional risk class for insured persons not classified in any DCG. Total: 15 risk classes.

Individuals can be classified in multiple DMECG risk classes at the same time, there is no limitation for specific combinations of DMECG risk classes.

- 5. Source of income interacted with age (SoI*age):** This risk adjuster is classified into 7 different socioeconomic statuses: fully disabled, other disabled, welfare recipients, self-employed, highly educated, students, and a reference group. Within each category, distinction is made on six age groups: 0-17, 18-34, 35-44, 45-54, 55-64, and 65-69 years. Except for the category students which only has the age group 18-34 and the highly educated group which has the distinction of age classes 18-44. An additional risk class is created for individuals 70+ years. Total: 36 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "SoI*Age". The model uses the SoI of individuals as of June 30th in the year prior.

- 6. Region:** The risk classes are not a geographical region but are groups of four-digit postal code areas²⁰. Total: 10 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "Region". The model uses the region of individuals as of June 30th in the year prior.

¹⁷The DDD is based by the WHO Collaboration Centre for Drug Statistics Methodology (WHO, 2024).

¹⁸In Dutch: Diagnose-behandelcombinatie (DBC).

¹⁹What DTC care product corresponds to what DCG class is more thoroughly explained in WOR 988 (2020b).

²⁰The classification of the postal code into a specific risk class is determined on characteristics such as the healthcare supply, socioeconomic conditions, and remaining health disparities in that postal code (Zorginstituut Nederland, 2022c).

-
7. **Socioeconomic status interacted with age (SES*age):** Four categories, very low, low, middle, and high, based on address income. Within each category, a distinction is made for the age group 0-17, 18-69, and 70+. Total: 12 risk classes.

The model uses the SES of individuals as of June 30th in the year prior.

8. **Household size interacted with age (HHS*age):** Four categories, residents of a long-term care institution²¹ as of this year, residents of a long-term care institution as of prior to this year, single-person households, and, all other households. Within each category, a distinction is made for the age groups 18-69, 70-79, and 80+. There is an additional risk class for those under 18. Total: 13 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "HHS*age". The model uses the HHS of individuals as of June 30th in the last year and the year before in case of being in a long-term care institution.

9. **Multiple-year high-cost groups (MYHCs):** Classification of insured into groups based on their cumulative costs over the previous three years. The threshold for classification is based on the top 15%, top 10%, top 7%, top 4%, top 1.5%, or top 0.5% costs compared to all other insured. There is an additional risk class for insured persons not classified in any of these multiple-year high-cost groups. Total: 9 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "MYHC".

10. **Physiotherapy diagnosis cost groups (PDCGs):** Classification of insureds into categories based on a chronic diagnosis with unlimited treatment duration as determined by declarations in the previous year. There is an additional risk class for the insured not assigned to any PDCGs. Total: 4 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "PDCG". In case someone has indications of diagnoses that are presented in multiple risk classes the risk class with the largest compensation is attributed to this individual.

11. **Prior spending on home care (PSHCs):** Classification of insured into groups based on their cumulative nursing and care costs over the previous three years. The threshold for classification is based on the top 3.5%, 3.0%, 2.5%, 2.0%, 1.5%, 1.0%, 0.5%, and 0.25% nursing and care costs compared to all other insured. Children (under 18) classified in the highest nursing and care category (top 0.25%) in the preceding year are in a separate risk class. There is an additional risk class for the insured not assigned to any PSHC. Total: 10 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "PSHC".

12. **Historical somatic morbidity (HSM):** Two categories, people who were classified with at least one somatic morbidity indicator (positive indication on a risk class in on of the

²¹Long term care is settled in a separate Healthcare Act, the Long Term Care Act (In Dutch: Wet Langdurige Zorg (wlz). The year prior to moving to long-term care institutions individuals are likely to have high healthcare costs. That is why moving into a long-term healthcare institution is considered in the HIA.

risk adjusters: PCG, DCG, PDCG, MYHCG, DMECG) in the past three years and people who have not been indicated with a somatic morbidity in the past three years. Total: 2 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "HSM".

13. **Multi-year pharmacy costs (MYPC):** Two categories, people who were classified with pharmacy costs in the top 25% at least once in the last three years and people who have not been classified in the top 25% pharmacy-based cost group in the past three years. Total: 2 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "MYPC".

14. **Indication of Pregnancy / Birth (IPB)** Two categories, people who have indications of pregnancy/birth and people without indication of pregnancy/birth in the past year. Individuals are considered to have indications of pregnancy/birth when declarations in maternity care. Total: 2 risk classes.

Each individual must score positive on one and only one risk class of the risk adjuster "IPB".

The morbidity risk adjusters and their corresponding risk classes are indicators. Note that the Ministry of VWS does have access to the costs made but does not have access to the medical information of all individuals. Therefore, the RE model uses prior usage of healthcare as a predictor of healthcare spending in year t . For example, individuals score positively on a PCG indicator when they use the minimum defined daily dose (DDD) for 180 days in a calendar year. As a result, when individuals do not reach 180DD in year $t-1$, the model does not capture the underlying medical issue.

4.2 Data preparation

This section describes the steps taken to prepare the data for analysis. To prepare the data I must first define the variables correctly for all three years. Next, I aggregated the healthcare expenditure for each unique Pseudo-BSN. Moreover, I annualized the healthcare expenditure for individuals who were not insured for a full year. Lastly, the data sets are cleaned and observations with administrative errors are removed.

Define variables:

As a first step, I construct all risk classes as dummy variables. Secondly, the somatic healthcare costs are given in eurocents. The costs for the various types of costs are therefore transformed from eurocents to euros.

Aggregation of observations with the same Pseudo-BSN:

Furthermore, individuals may have changed health insurers and therefore have had multiple contracts in the same year. All individuals that have multiple contracts in one year are therefore duplicated in the dataset. The duplicated records are compromised to one observation. I aggregate the dataset on the unique pseudo-BSN and risk characteristics. In the subsequent parts of this study, the prevalence of any group is consistently measured in insured years, rather than the total number of contracts.

Annualization of healthcare expenditure:

Individuals may have stopped their health insurance at any point during the year because of death or migration. Therefore, in all analyses, I follow the procedure of annualizing healthcare expenditures.

Next, the individual level expenditures are annualized and weighted by the fraction of the year an individual was enrolled. Therefore I use the variable 'weight' as the fraction of the year the individual was enrolled in health insurance²². Using annualized costs prevents the underestimation of somatic healthcare expenditure for individuals who are not insured during the full year.

Cleaning the dataset:

Some observations display negative costs. This is considered an administration error and these individuals are removed from the dataset. Moreover, some observations display missing costs. These observations are also dropped from the dataset.

Lastly, in each dataset, there are individuals with a weight larger than 1, which would suggest that they are insured for more than a full year. This is considered an administration error, so these weights are set equal to 1.

4.3 Descriptive statistics

Table 4.1 shows the descriptive statistics after data preparation.

4.3.1 Descriptive statistics on sample level

Table 4.1: Descriptive statistics on healthcare costs (made representative for 2021-2023)

²²An example of the the annualization is as follows: Suppose an individual is insured for 50 days of the year in 2021. The weight of this individual can be calculated as follows: $50/365=0.14$. Therefore the expenditure of these individuals is annualized by dividing the actual costs by this person's weight. Suppose this person had €650 healthcare cost in these 50 days. The annualized costs would then be $650/0.14= €4642$.

Metric	2021	2022	2023
# of contracts	17,321,702	17,431,601	17,497,406
# of individuals	17,256,313	17,365,572	17,437,779
# of insured years	16,951,713	17,058,689	17,148,230
Total expenditure (in billion €)	40.817	42.405	40.772
Mean spending (€)	2,407.82	2,485.82	2,377.60
Standard deviation (€)	8,704.38	8,895.51	9,095.63
Minimum (€)	0.00	0.00	0.00
Maximum (€)	8,890,455	10,173,408	10,207,420
Median (€)	462.13	489.99	443.47

The number of insured years increases slightly over time as the Dutch population is growing. The mean healthcare spending is relatively constant over 2021-2023. The healthcare costs display a positive skew. There is a large right tail indicating that there are individuals with very high expenditure relative to the rest of the individuals in the dataset. This can be observed by comparing the maximum healthcare costs with the mean and median healthcare costs. The mean exceeds the median, indicating a positive skew. Additionally, the maximum value is a lot larger, further highlighting the skewness.

Chapter 5. Methodology

This thesis tests if the utility of healthcare insurers is different for different subgroups of individuals. The goals of our analyses are 1) to quantify the heteroscedasticity of residual spending across and within selective subgroups of insured and 2) to approximate its potential effect on the utility for healthcare insurers by applying the findings to the utility framework as described in the previous section, ultimately applying MPT (see equation 3.11 and 3.1). This section describes methods used to achieve these goals.

5.1 Estimation of the risk equalization model

The ex-ante compensation rewarded to health insurers is the sum of the expected healthcare cost of each individual in their portfolio for that year. The expected healthcare costs are estimated using an OLS regression for each year, equation 5.1. The OLS aims to minimize ϵ with respect to β .

$$\hat{y}_i = \sum_{j=1}^M x_{ij} * \beta_j + \epsilon_i \quad (5.1)$$

The compensation an insurer gets per individual is the expected healthcare cost \hat{y}_i i.e, the fitted value $\sum x_{ij}\beta_j$. Where x_{ij} is a binary variable, with j representing the risk class (M=233 risk classes in total) and i representing a unique individual. The β_j represents the compensation for the risk class j. The ϵ_i represents the residual spending for individual i. The average of the fitted value $\sum x_{ij}\beta_j$ - the actual costs are zero per definition for each subgroup, given the characteristics of the OLS. The risk adjusters are used to predict individual level spending. The Dutch RE model is estimated using an OLS regression model based on those risk classes The application of OLS is highly interpretable on an individual level The coefficient β_j is interpreted as the ceteris paribus change in predicted annualized healthcare expenditure for an individual and thus the change in ex-ante compensation rewarded to an insurer, given that the indicator variable equals 1.

Restrictions in the estimation model

The OLS estimation model as depicted in equation 5.1 is subject to constraints 5.2, 5.3, and, 5.4.

The first restriction indicates that the risk adjuster "Gender*Age" exactly distributes the total Macro Performance Amount (MPA). This ensures that the "Gender*Age" variable sets the predictable healthcare costs and the other risk classes can increase or diminish that amount.

$$\sum_{i=1}^N w_i \sum_{j=1}^L \hat{B}_{AgeGender(j)} x_{i, AgeGender(j)} = \sum_{i=1}^N y_i \quad (5.2)$$

Where: AgeGender(j): illustrates the unique risk classes within the variable "Age and Gender". The 42 risk classes within the variable "Age and Gender" are denoted by 'L'.

Additionally, the following two restrictions are applied to ensure that the sum result for each risk adjuster adds up to exactly 0.

$$\sum_{i=1}^N w_i \sum_{j \in \kappa} \hat{B}_{k(j)} x_{i,k(j)} = 0, \quad (5.3)$$

$$\kappa = \{PCG, DCG, DMECG, Region, MYHC, PDCG, PSHC, HSM, MYPC, IPB\}$$

$$\sum_{i=1}^N w_i \sum_{Age,j \in \rho} \hat{B}_{\rho(Age,j)} x_{i,\Psi(Age,j)} = 0, \quad (5.4)$$

$$\rho = \{SoI, SES, HHS\}$$

Note that for all variables except the PCGs, DCGs, and MDECGs, individuals can only score positive on one indicator per variable. However, for the PCG, DCG, and MDECG individuals can have indications of more than one as they can use multiple medications, have multiple diagnoses, use multiple forms of aid equipment. Therefore, the residual spending does not per definition add to 0 when only looking at specific risk classes within these variables.

Estimation of residual spending

Residual spending is determined as the difference between the expected and actual costs on an individual level.

$$Residualspending_i = \hat{y}_i - y_i \quad (5.5)$$

5.2 Analysis of the distribution of residual spending

Distribution of residual spending for people that are undercompensated vs. people that are overcompensated

Individuals that score positive on one of the morbidity indicators are more prone to undercompensation and the residual spending is more pertinent for individuals who are prone to undercompensation (Equalis, 2023; Oskam et al., 2024; Withagen-Koster et al., 2018). Therefore, I created subgroups for people who were undercompensated and overcompensated in year 2021, 2022, and 2023. I compare the residual spending patterns between people who were never undercompensated, once undercompensated, twice undercompensated or three times undercompensated in three years. I compare whether there are striking differences in the residual spending distribution between these groups.

Distribution of residual spending for a specific risk class

Furthermore, the residual spending is compared at the subgroup level to determine if there are differences in residual spending between different subgroups of insured. The predefined risk adjusters and the risk classes are used to create specific groups of insureds. The difference in residual spending is tested using Levene's test, testing the equality of variances.

Levene's test is a statistical test based on deviations from the group mean. The test statistic follows an f-distribution under the null hypothesis. The null hypothesis states that the variances are equal between two (or more) groups. Consequently, when the p-value is less than the chosen significance level I will reject the null hypothesis and conclude there is a significant difference in the variances between the groups. In this thesis, I reject the null hypothesis for all p-values smaller than $p = 0.05$.

Levene's test allows to compare multiple groups while the f-test maximally can compare 2 groups. Furthermore, Levene's test does not require data to be normally distributed (unlike the f-test). Therefore it is robust to normality violations.

Concluding, Levene's test is used to analyze whether the standard deviation of ϵ is significantly different across subgroups (i.e., whether there is heteroscedasticity of residual spending). Consequently, the variances are tested if they are consistent over the years 2021, 2022 and 2023.

Risk premia required following significant heteroscedasticity of residual spending

In case of significant differences in the residual spending between different subgroups of insured, the differences in the required risk premium of these subgroups are calculated using MPT. The variance of residual spending is considered a difference in the variance of the return on investment as described in the theoretical framework. The degree of utility differences depends on the magnitude of the risk aversion and the magnitude of the residual spending. In the case that healthcare insurers are risk averse, significant differences in the residual spending between groups indicate that the utility enjoyed by signing individuals into an insurance policy is not equal for individuals from different subgroups of insured. However, the degree of risk aversion is rather arbitrary. Therefore, I argue to apply a wide range of risk aversion and interpret the sensitivity of the risk premiums. As discussed in the theoretical framework, I assume that health insurers are risk averse. Specifically, ($\alpha > 0$) ranging between 0,01 to 0,10.

The risk aversion values, together with the estimated differences in residual spending, will be applied to calculate the risk premia, following equation 3.11. Multiple values in the identified risk aversion range are applied in the utility function to determine the difference in the utility for insurers for different subgroups of insured. These scenario analyses will showcase the impact of the levels of risk aversion on the equalization principle if there is a significant difference in the residual spending between subgroups of insured.

Chapter 6. Results

This section presents the results of the analysis on heteroscedasticity in residual spending within the Dutch health insurance market. The findings are structured around the main research questions and the hypothesis of the respective sub-questions.

6.1 Replication of the risk equalization model

First, I replicate the RE model for the years 2021, 2022, and 2023 using the OLS with the restrictions, as posed in the methodology (equation 5.1 - 5.4). Following this, I determine the total predicted medical costs (i.e. ex-ante compensation) for the years 2021, 2022, and 2023. Lastly, I determine the residual spending which is the actual spending minus the predicted spending, as described in the methodology (equation 5.5). For perfect equalization, the residual spending amounts to €0. The residual spending and its standard deviations for 2021-2023 are displayed in table 6.1. Lastly, I merge the datasets of 2021, 2022, and 2023 into one dataset.

Table 6.1: Summary statistics of residual spending (2021-2023)

Metric	2021	2022	2023
# of Insured years	16,951,713	17,058,689	17,148,230
Residual spending (€)	0.00	0.00	0.00
Standard deviation (€)	6,971.94	7,124.32	7,405.73

6.2 Distribution of residual spending for people that are under-compensated vs. people that are overcompensated

I analyze the aggregated data to see if there are any discrepancies in the distribution of residual spending between people who are overcompensated vs. people who are undercompensated. Therefore, I construct groups of people who have been undercompensated and/or overcompensated in each year. Next, I analyze the frequency of which individuals have been under/overcompensation in the period 2021-2023, see figure 6.1. The frequency on the vertical axis indicates the percentage of the population per level of residual spending. The distribution of residual spending of people who have never been undercompensated (i.e. always overcompensated) is more narrowly distributed than the people who have been undercompensated once, twice, or three times over the period 2021-2023. This suggests that the variance of residual spending is higher for individuals that are undercompensated. The individuals overcompensated for one or more years in 2021-2023 exhibit a more widely dispersed distribution. Overall, the majority of all insured years have been slightly overcompensated over the period 2021-2023.

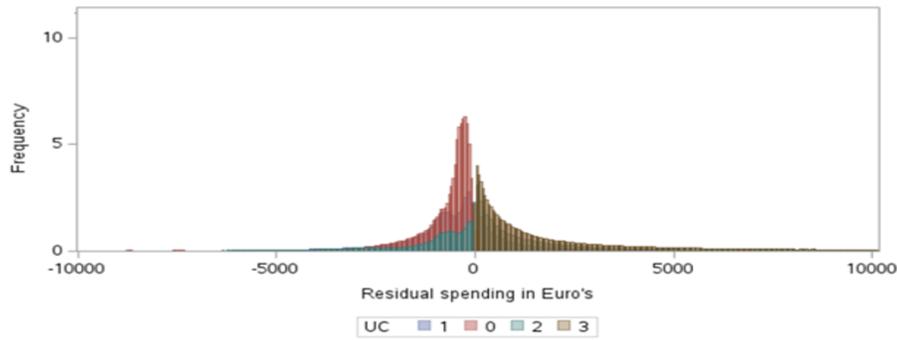


Figure 6.1: Total compensation over the years 2021-2023 per individual and the number of times someone was undercompensated during these three years.

UC 0: Individuals who were never undercompensated in 2021, 2022, or 2023 (i.e., always overcompensated).

UC 1: Individuals who were undercompensated once in 2021, 2022, or 2023 (i.e., overcompensated twice).

UC 2: Individuals who were undercompensated twice in 2021, 2022, or 2023 (i.e., overcompensated once).

UC 3: Individuals who were undercompensated in all three years: 2021, 2022, and 2023 (i.e., never overcompensated).

6.3 Distribution of residual spending for a specific risk class

The risk adjusters and risk classes from the RE model are used to create a specific group of insured to analyze in this thesis. The goal is to provide in detail how the distribution of residual spending is portrayed for specific groups of insured. The number of insured years, the residual spending, and the standard deviation of residual spending for all 233 risk classes in the 14 risk adjuster variables for the year 2023 are displayed in tables 1-14 in appendix D.

As discussed in the literature review it would be most interesting to investigate if there are differences in residual spending distributions between subgroups that are prone to under and overcompensation. Furthermore, the goal of this thesis is to investigate the degree of residual spending in more detail compared to the paper by Oskam et al. (2024). Oskam et al. (2024) found that individuals who have positive morbidity indicators are more likely to be undercompensated than individuals without morbidity indicators. Therefore the morbidity indicators (PCG, DCG, DMECG, HSM, MYHC) are particularly interesting to investigate the pattern of residual spending. Moreover, Withagen-Koster et al. (2023) emphasizes the importance of predictability for heteroscedasticity to be a potential source of risk selection incentives. I assume that the morbidity indicators PCG, DCG, and, DMECG show a larger degree of predictability in the cost claims made as these indications are hinged on specific diseases. Therefore, I will look specifically into a risk class from the PCG.

Within the risk adjuster "PCG" the indications of Cancer (add-on), Pulmonary Arterial Hypertension, and kidney diseases show the largest standard deviations (Appendix D, table 2). Cancer is divided into two risk classes and the latter is an add-on class that consists of very specific and expensive medications. The risk class indicating Pulmonary Arterial Hypertension

has a smaller group size compared to the cancer add-on risk class and kidney diseases risk class. Moreover, there have been changes in the definition of the risk class of Pulmonary Arterial Hypertension from 2021-2023 as a result of the inclusion of the risk adjusters HSM and MYPC (Rijksoverheid, 2022).

I decided to further investigate the distribution of residual spending for the PCG indication kidney diseases²³.

6.3.1 Residual spending for pharmaceutical indication of kidney diseases

Table 6.2 shows the prevalences of kidney diseases in the RE model, the mean residual spending in 2021-2023, and the standard deviation.

Table 6.2: Mean residual spending and standard deviation for kidney disorders vs. no PCG indicator from 2021 to 2023

Year	Risk class	Insured years (#)	Mean residual spending (€)	Std. dev. (€)
2021	No PCG indicator (PCG 0)	13,109,564	3.49	5,522.50
	Kidney disease (PCG 25)	9,016	3.49	32,646.16
2022	No PCG indicator (PCG 0)	14,451,869	12.01	5,645.01
	Kidney disease (PCG 25)	5,661	12.01	32,979.55
2023	No PCG indicator (PCG 0)	12,673,258	17.83	5,671.22
	Kidney disease (PCG 30)	5,316	17.83	32,403.76

The number of people with kidney disease indications based on the RE model has decreased from 2021 to 2022 and 2023. The definition of kidney diseases, medication, and the DDD have remained consistent over the years 2021-2023 (Zorginstituut Nederland, 2020a, 2021a, 2022a). It could be the case that there are fewer people with kidney diseases. However, this option seems unlikely as the number of people with kidney diseases is on a rising trend²⁴ (Francis et al., 2024). Possible reasons for the decline of insured years that score positive on this risk class over 2021-2023 as observed from table 6.2 may be because of changes in the prescription of medicine.

The following figures depict the distribution of residual spending for individuals who score positively on the pharmaceutical indication of kidney diseases vs. the individuals who do not score positively on any pharmaceutical indication of kidney diseases.

²³The risk class PCG25 in 2021 and 2022, PCG30 in 2023 corresponds to the pharmaceutical indication of kidney diseases (ESHPM, 2020a, 2021, 2022).

²⁴Kidney diseases are the third fastest growing cause of death worldwide.

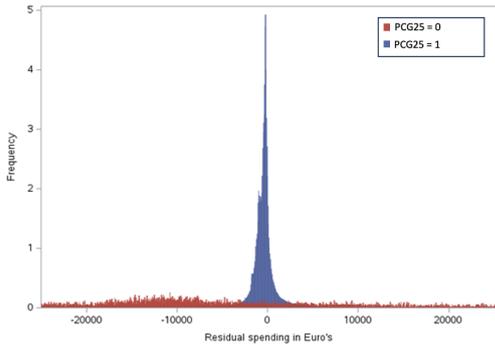


Figure 6.2: Distribution of residual spending - PCG risk class corresponding with kidney diseases 2021.

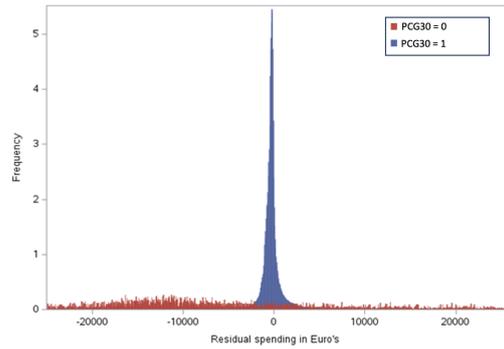


Figure 6.4: Distribution of residual spending - PCG risk class corresponding with kidney diseases 2023.

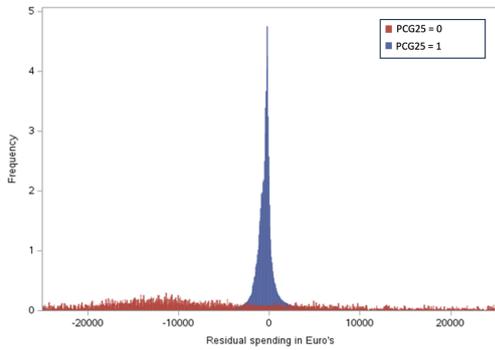


Figure 6.3: Distribution of residual spending - PCG risk class corresponding with kidney diseases 2022.

The distribution representing the pharmaceutical indication of kidney diseases has a larger deviation than the distribution of the group of individuals without any positive pharmacy cost group indicator. Moreover, the frequency of residual spending on kidney disorders is highest for negative residual spending. At the same time, the frequency in the group with no pharmacy cost group indication has a sharp frequency around the perfect equalization. Furthermore, it is interesting to see that the distribution of no pharmacy cost indicators has a smaller distribution but has more outliers compared to the group with indications of kidney disorders. The figures 3.2-3.4 do not show the whole array of the distribution, the outliers can be observed far outside of the set borders. The differences between the kidney disorder indication group and the group with no pharmacy cost group indication seem to be distinctively different from each other.

Consequently, when I perform a statistical test of equal variances (Levene's test), I conclude that the variance of residual spending for the risk class corresponding to the pharmaceutical indication of kidney diseases is statistically different from the variance of residual spending for the risk class corresponding to no positive pharmacy indication, $p = 0.0001$ ($p < 0.05$), *ceteris paribus*. I find this result for 2021, 2022, and, 2023.

The results are robust to the specification of the statistical test. Applying both f-tests and Levene's tests yielded consistent results, reinforcing the reliability of the findings.

6.3.2 Consistency of residual spending for pharmaceutical indication of kidney diseases over time

When I compare the residual spending patterns over the three years I conclude that the residual spending of the risk class with a pharmaceutical indication of kidney diseases follows a similar distribution of residual spending over 2021-2023. This is depicted in the figure below:

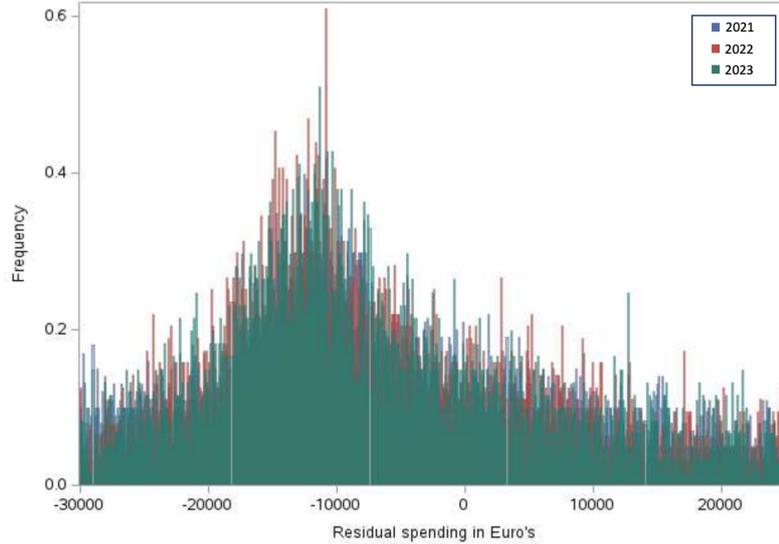


Figure 6.5: Residual spending distribution for positive indication of pharmaceutical cost group "kidney diseases" for 2021-2023.

The distribution of kidney diseases shows a sharp increase in frequency for residual spending of approximately -€12,500 for all three years²⁵. The spike in prevalences in this range may indicate underlying characteristics driving similarities in residual spending patterns away from the point of perfect equalization. When I use Levene's test for testing the homogeneity of variances I find that we cannot reject the null hypothesis of homogeneity of variances as $p = 0.8652$ ($p < 0.05$). There is not enough evidence to reject the null hypothesis that the variation in residual spending is consistent over the years 2021-2023.

Since there is not enough evidence to suggest that the variation of residual spending over 2021-2023 is different it is assumed that the variation of residual spending remains consistent for these years. A constant variation indicates that the variance in the residual spending over time is predictable.

6.3.3 Underlying characteristics driving residual spending within kidney diseases

This section dives further into the drivers of residual spending within kidney diseases. I compare the residual spending of underlying characteristics of individuals with positive indications on the pharmaceutical cost group associated with kidney diseases.

²⁵Negative residual spending indicates a profit for the insurer.

Research by Vervloet et al. (2023) shows that the groups of people with kidney diseases are overrepresented by female patients (57%). Furthermore, the average age of people with chronic kidney diseases is 72 years. People with kidney diseases are often seen to have multiple co-morbidities. Diabetes is especially a prevalent co-morbidity for people with kidney diseases. Approximately 23% of all people with kidney diseases have diabetes mellitus II (Vervloet et al., 2023). Simultaneously, diabetes plays a notable role in the causation of kidney diseases (Kumar et al., 2023). Moreover, the mean age of all people with kidney diseases is 72 years old. However, when in combination with other diseases (co-morbidities) these statistics change. For example, the average age of people with kidney disease with heart failure as a co-morbidity is 81 years old, which is 9 years older than in the case of all people with kidney diseases (Vervloet et al., 2023). Similarly, more co-morbidities are observed patients that are older.

This information is taken into consideration when investigating patterns underlying the variation of residual spending within the risk class. Therefore, I look into the dispersion of residual spending for men and women with kidney diseases. Next, I compare young (-65 years) and elderly (+65 years). Lastly, I compare the distribution of residual spending for individuals with kidney diseases and co-morbidities such as diabetes mellitus. These underlying characteristics may be driving the heteroscedasticity in residual spending within the risk class corresponding with kidney diseases

Gender differentiation in residual spending for pharmaceutical indication of kidney diseases

Of all individuals who are classified into the indication of kidney disease based on pharmaceuticals 49.9% are male and 51.1% are female. The distribution is more widely dispersed for males (figure 6.6). Levene's test shows a p-value of 0.0001 ($p < 0.05$). Therefore, I reject the null hypothesis of equality of variances.

This indicates that differences in residual spending may be predictably driven by gender differences. The reason that gender may be a driver of predictable differences could be due to different presentations of kidney diseases in women and men.

Age differentiation in residual spending for pharmaceutical indication of kidney diseases

When comparing the residual spending patterns of a positive pharmaceutical indication of kidney diseases (PCG 30 = 1, in 2023) it is observed that the distribution is generally similar but does show differences between individuals being 65+ years and individuals being 65- years (figure 6.7). There are 1,089 individuals with a positive classification of PCG30 who are 65- and 4,985 individuals who are 65+ or older. The distribution is more widely dispersed for the 65+ group. Levene's test shows a p-value of 0.0143 ($p < 0.05$). Therefore, I reject the null hypothesis of equality of variances.

This indicates that differences in residual spending for individuals with pharmaceutical indications of kidney diseases may be predictably driven by age differences. Age may be a driver of predictable differences in residual spending for individuals with a pharmaceutical indication

of kidney diseases because the life expectancy of people with kidney diseases is significantly compromised (Nierstichting, n.d.).

Co-morbidity differentiation in residual spending for pharmaceutical indication of kidney diseases

When comparing the residual spending patterns of a positive pharmaceutical indication of kidney diseases (PCG 30 = 1, in 2023) I find that the distribution is quite similar (figure 6.8). There are 1,893 individuals with a positive classification of PCG 30 and with a positive classification of DCG3, among which diabetes is one of the diagnoses. There are 4,181 individuals with no indication of any diagnosis cost group.

The distribution is more widely dispersed for the individuals with the positive diagnosis risk group. Levene's test shows a p-value of 0.385 ($p > 0.05$). Therefore, I do not reject the null hypothesis of equality of variances. The indication of diagnosis group DCG3, does not seem to drive heteroscedasticity of residual spending for individuals with a positive indication of kidney diseases.

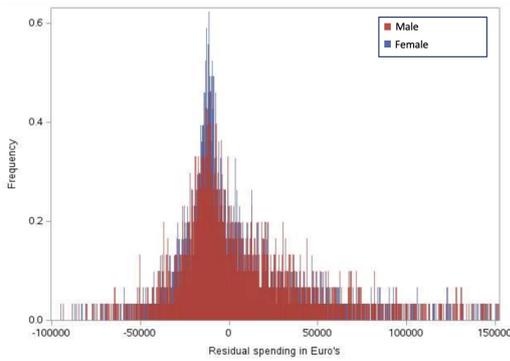


Figure 6.6: Distribution of residual spending for "gender" within PCG risk class corresponding with kidney diseases - 2023.

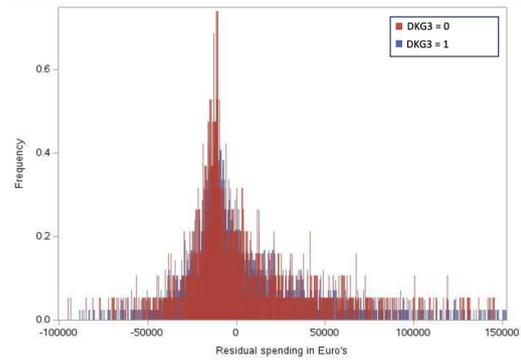


Figure 6.8: Distribution of residual spending for co-morbidity within PCG risk class corresponding with kidney diseases - 2023.

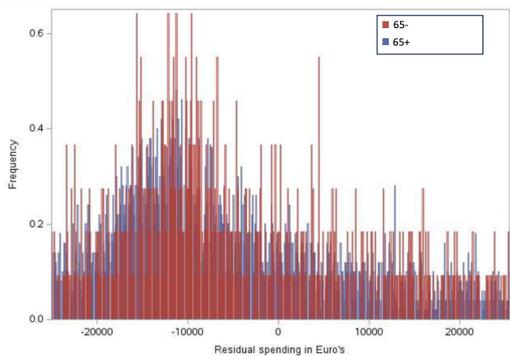


Figure 6.7: Distribution of residual spending for "age" within PCG risk class corresponding with kidney diseases - 2023.

6.4 Risk premia required to compensate financial risk as a consequence of heteroscedasticity of residual spending

Following equation 3.11, I determine the required risk premium using residual spending and the risk aversion level. Equation 3.11 determines the required risk premium for a risk class as a whole. Therefore, I divide by the number of individuals per risk class to obtain the risk premium per person per risk class.

6.4.1 Risk premium required for individuals with a pharmaceutical indication of kidney disease

Table 6.3 displays the risk premium required per person for people with a positive pharmaceutical indication of kidney diseases ($PCG30 = 1$).

Table 6.3: Risk premia - sensitivity analysis for PCG30

Risk class / Risk aversion	0.01	0.02	0.09	0.10
Risk premium for PCG30 = 1	€ 1,128.27	€ 2,256.54	€ 10,154.41	€ 11,282.68
% change in required compensation	+10.89%	+21.77%	+97.98%	+108.86%

The required risk premium is relatively large compared to the current compensation. The compensation insurers receive for an individual with a positive indication of PCG30 in 2023 is €10,363.92. For a risk aversion level of 0.01, the required compensation amounts to €1,128.27, which entails a percentual increase of 10.89% compared to the current compensation. For higher risk aversion levels, the required compensation and the percentual increase compared to the current compensation are even larger. This seems unreasonable, as the incentives to risk selection do not seem as obvious in the current state that such large risk premia would be required. Therefore, potentially even smaller risk aversion levels would be appropriate. However, further research must determine the risk aversion level most appropriate to the Dutch health insurers market.

Risk premiums required for individuals with a pharmaceutical indication of kidney disease - adjusted standard deviations

The method applied in the previous section results in a required risk premium for all risk classes²⁶. However, this seems highly impracticable. Rather one can argue that the current compensations are already quite adequate, at least to a certain degree of variance. Therefore, one could argue that the risk premium should be based on the variance exceeding a 'normal' variance. To exemplify I used the average standard deviation in residual spending of the whole population in 2023 as a benchmark to observe the excessive standard deviation in other risk classes. I compute the adjusted standard deviation for each risk class by subtracting the average standard deviation of residual spending in 2023 from the standard deviation of each specific risk class. Consequently, the adjusted standard deviation of residual spending for each risk class

²⁶All risk classes portray some variance and according to the model therefore all risk classes would require some risk premium to compensate the variance. The risk premium would be very small for most risk classes.

decreases by 7,405.73. Therefore, the adjusted standard deviation results in a smaller variance and logically a smaller risk premium required for the risk classes. In some cases, the adjusted standard deviation is negative and will result in a risk discount of the compensation of that risk class. Alternatively, one could argue that the risk class with the lowest standard deviation could be taken into consideration as the benchmark to observe excessive standard deviation in residual spending.

Take, for instance, the example of the pharmaceutical indication for kidney diseases. Table 6.4 shows that the risk premium is substantially smaller when using an adjusted standard deviation compared to the risk premium shown in table 6.3 which considers absolute standard deviations.

Table 6.4: Risk premia computed with adjusted standard deviations - sensitivity analysis for PCG30

Risk class / Risk aversion	0.01	0.02	0.09	0.10
Risk premium for PCG30=1	€ 697.37	€ 1,394.73	€ 6,276.31	€ 6,973.67
% change in required compensation	+6,73%	+13,46%	+60,56%	+67,29%

6.4.2 Risk premium required for all risk classes

Similarly, the risk premia for all 233 risk classes have been computed in appendix E.

Using the absolute standard deviations all risk classes require a premium to the current compensation to address the risk of volatility of residual spending. For most risk classes, the risk premia required is close to €0. This means that these risk classes²⁷ are adequately compensated for the risk of variance in residual spending. In total, 129 risk classes require a risk premium that is below 1% of the current compensation attributed to that specific risk class, given alpha = 0.01. This means that 129 out of 233 risk classes (55%) are adequately compensated for alpha = 0.01. The other risk classes require a relatively larger risk premium to address the volatility of residual spending.

There are 76 risk classes that require a premium of 1%-10% of the current compensations attributed to that specific risk class, if the heteroscedasticity of that group is significant, given alpha = 0.01. This means that 76 out of 233 risk classes (33%) require a moderately high premium compensation compared to the current compensation.

There are 11 risk classes that require a premium of 10%-20% of the current compensations attributed to that specific risk class, if the heteroscedasticity of that group is significant, given alpha = 0.01. This means that 11 out of 233 risk classes (5%) require a high premium compensation compared to the current compensation.

There are 17 risk classes that require a premium of more than 20% of the current compensations attributed to that specific risk class, if the heteroscedasticity of that group is significant, given alpha = 0.01. This means that 17 out of 233 risk classes (7%) require a high premium compensation compared to their current compensation.

²⁷Gender*age (except for newborns in this year), Sol*age (except low income for young people), Region, SES*age, HHS*age (except young and middle-aged people transferring to the long term care act), HSM, MYPC and IPB.

Risk premiums required for all risk classes - adjusted standard deviations

When using the adjusted standard deviations instead of the absolute standard deviations, not all risk classes require a premium to the current compensation to address the risk of volatility of residual spending. Rather, risk classes with standard deviations smaller than the standard deviations require a risk discount. The results of the risk premiums and discounts for each risk class using the adjusted standard deviation are portrayed in appendix F.

In total, 184 risk classes require a risk premium that is below 1% of the current compensation attributed to that specific risk class, given alpha 0.01. Even more so, 57 risk classes portray a negative risk premium, all but one within the range of -1% to 0%. This means that 183 out of 233 risk classes (79%) are adequately compensated and one risk class requires a moderate negative premium,²⁸ for alpha = 0.01.

There are 35 risk classes that require a premium of 1%-10% of the current compensations attributed to that specific risk class, given alpha = 0.01. This means that 35 out of 233 risk classes (15%) require a moderately high premium compensation compared to the current compensation.

There are 6 risk classes that require a premium of 10%-20% of the current compensations attributed to that specific risk class, given alpha = 0.01. This means that 6 out of 233 risk classes (3%) require a high premium compensation compared to the current compensation.

There are 8 risk classes that require a premium of more than 20% of the current compensations attributed to that specific risk class, given alpha = 0.01. This means that 8 out of 233 risk classes (3%) require a high premium compensation compared to their current compensation.

²⁸SoI* Age 33: Reference group 35-44 years old is the only risk class that would require a risk discount larger than 1% of the current compensation given for that risk class.

Chapter 7. Discussion and conclusion

7.1 Discussion

This thesis has thoroughly examined the financial dynamics and implications of heteroscedasticity in residual spending within the Dutch health insurance market, focusing on eliminating the sources of incentives for risk selection. The primary research question was to what extent the variance of residual spending within subgroups of insured individuals contributes to incentives for risk selection in the health insurers market.

The study confirms significant heteroscedasticity in residual spending for various risk classes, notably pharmaceutical indication of kidney diseases vs no pharmaceutical indication of disease. Indicating that insurers face different levels of financial risk across risk classes. Therefore, the findings of this thesis confirm the first hypothesis.

H1: Incentives for risk selection remain through differences in the variance of the residual spending for subgroups of insured, subject to the degree of risk aversion of health insurers.

The standard deviation for residual spending in the risk class with a pharmaceutical indication of kidney disease was consistently higher compared to the risk class with no pharmaceutical indication of any disease, over the years 2021-2023. This suggests a greater financial risk for insurers for enrollees from the first risk class compared to the latter. These findings support the hypothesis that heteroscedasticity in residual spending is a significant factor in risk selection incentives. This aligns with the recent study by Oskam et al. (2024), which also identified significant variances in healthcare spending as a potential driver for risk selection. The heteroscedasticity of residual spending necessitates a more nuanced approach to determining the compensation emerging from the RE model to adhere to the equalization principle.

The elimination of risk selection incentives is crucial for promoting efficiency, high quality, and equality of care. The significant heteroscedasticity found for kidney diseases and other risk classes confirms the need for insurers to be compensated for the financial risks posed by these variances. Using Modern Portfolio Theory (MPT), the required risk premiums to offset the financial risk of heteroscedastic residual spending were calculated. These premiums vary significantly based on risk aversion levels. The risk class with kidney diseases is among the risk classes requiring high relative premiums. This validates the second hypothesis .

H2: Assuming insurers are risk averse, health insurers require a risk premium to compensate for variance in residual spending. The required premium is dependent on the magnitude of the variance. The variance is expected to be higher for subgroups with higher healthcare expenditures. The required risk premium is expected to be higher for groups of insured that are high healthcare consumers compared to groups that use relatively little healthcare..

Specifically, the results confirm that larger risk premia are required for subgroups of insured that portray relatively high healthcare consumption due to a morbidity indicator on

specific PCGs, DCGs, or DMECGs. Moreover, the study identified that residual spending for kidney diseases remained constant over 2021-2023, suggesting predictability. This predictability is essential as it highlights that heteroscedasticity is a reliable source of risk selection incentives.

Specific underlying characteristics, such as age and gender, were found to drive the heteroscedasticity of residual spending within kidney diseases in 2023. This partially confirms the third hypothesis.

H3: The distribution of residual spending in a risk class may be driven by specific underlying characteristics. Individuals with higher predicted costs in other categories are hypothesized to cause larger within-group differences in residual spending.

The distribution of residual spending does seem to be driven by positive indications on other risk classes. This is true for age and gender in this specific example but does not hold for highly prevalent co-morbidities. This finding suggests that the interaction of age and gender within morbidity indicators may be of more importance than initially anticipated.

7.1.1 Robustness

The differences in the variance of residual spending between different risk classes are consistent over 2021-2023. Moreover, the findings of this thesis are robust to the specification of the statistical test, validated by consistent results across different statistical tests (f-test and Levene's test).

7.1.2 Implications

There is a need for policy adjustments to better compensate health insurers for the financial risks posed by heteroscedasticity of residual spending. Based on the analysis, it is recommended that policymakers adjust the risk equalization model to account for the variances between different risk classes in residual spending. This can be achieved by introducing risk premiums to better reflect the financial risks faced by insurers, particularly for high-risk classes such as kidney diseases.

Depending on either using absolute or adjusted standard deviations and the chosen risk aversion, the majority of the risk classes are adequately compensated for the variance of residual spending. However, several risk classes require a high risk premium to address the variance of residual spending. There are 11 risk classes that require a premium of 10%-20% and there are 17 risk classes that require a premium of more than 20% of their current compensations, assuming a risk aversion of $\alpha = 0.01$ and using absolute standard deviations. This means that 28 out of 233 risk classes (12%) require a high to very high premium compensation compared to the current compensation.

7.1.3 Limitations

Limitations include the assumption of Constant Absolute Risk Aversion (CARA), the magnitude of risk aversion levels, highlighting the need for more empirical data on risk aversion specific to

the Dutch health insurance market, and the actual effect heteroscedasticity of residual spending on health insurers partaking in risk selection.

First of all, one could argue that the CARA assumption does not hold and should rather consider the CRRA assumption. The CRRA assumption argues that risk aversion is dependent on the initial wealth. Using CRRA would imply the risk premia are dependent on the wealth/magnitude of each insurer and therefore different for larger/smaller insurers. Consequently, when we apply the CARA assumption naturally the larger insurers are at a slight advantage. Therefore, using the CARA assumption to determine the risk premium required might incentivize market consolidation as a result.

Secondly, the risk aversion level chosen in this thesis is rather arbitrary. There is little to no research on the risk aversion levels portrayed by health insurers operating in a regulated market. However, the findings of this paper are contingent on the assumption that health insurers are risk-averse.

Thirdly, even if health insurers are proven to be risk averse the actual incentive to risk selection might be dampened. While the heteroscedasticity of residual spending theoretically poses a source of selection incentives, its practical impact may be limited. In order to perform risk selection the insurers must actively research which groups to target, then actively market to that group, for which they will risk an ethically questioned reputation. Therefore, the proposed additional risk premium might not be necessary, as the incentive for risk selection could be of smaller importance than suggested in this thesis.

Lastly, the hypotheses and conclusions are specific to the Dutch health insurance market. Similar systems in other countries may yield different results due to varying market dynamics and regulations.

7.1.4 Recommendations for future research

Future research should focus on exploring measures of risk aversion that reflect the realities of the health insurance market. Furthermore, is needed to investigate the underlying characteristics driving the heteroscedasticity of residual spending. Moreover, future research must point out if there is a relation between segmentation of the market and heteroscedasticity of residual spending. From a practical point of view, future research must investigate what level of variance of residual spending would be used as a benchmark to practically be able to implement the risk premia.

First of all, further research is required to identify the actual risk aversion levels present in the Dutch health insurance market.

Secondly, further research is necessary to investigate the exact drivers of residual spending for each risk class. A more thorough understanding of the drivers of the variation in residual spending within risk classes contributes to identifying more targeted approaches for compensating for these risks. The results show that heterogeneity of residual spending within the risk

class for kidney diseases may be driven by gender and age. Possibly, an interaction of the age and gender variable with the morbidity indicators might portray a more accurate estimation instead of the summation of the compensation of the age and gender variable and the morbidity variable.

Thirdly, this study did not have data available to analyze the distribution of patients over different insurers. Therefore, future research must investigate if risk classes with high variance of residual spending are more segmented in the market compared to risk classes with low variance in residual spending. Moreover, the question remains to what extent heteroskedasticity of residual spending is an actual problem if the group of patients from any risk class with a high variance of residual spending would be evenly distributed across the different health insurers. As discussed in the introduction, Geruso and Layton (2017) argues that even the absence of segmentation does not necessarily imply the absence of risk selection. Risk selection may present through underserved markets due to all insurers disproportionately underinvesting in certain healthcare in order to dissuade enrollees from risk classes with higher financial risks. In this case, further research would be necessary to identify risk selection actions through investigating the strategic over and underinvestment in specific risk classes.

Lastly, it seems practically unlikely to impose a risk premium to all risk classes, therefore research is needed to determine from what levels of variances a risk premium would be required. This thesis proposes the adjusted standard deviation as a threshold to determine what level of variance would normally be acceptable within the previous model. Moreover, this could be qualitatively benchmarked with actuarial studies assessing the magnitude of the risk premiums required by insurers in different industries to contract individuals with increased risk. To provide a more adequate evaluation of a normally acceptable variance a qualitative study amongst policymakers and insurers would be necessary.

7.2 Conclusion

In conclusion, this thesis underscores the importance of addressing the variance of residual spending to eliminate risk selection incentives. The risk premiums calculated in this thesis serve as a proxy to identify which specific risk classes require adjustments and to estimate the approximate magnitude of those adjustments. By refining compensation models for risk through variances in residual spending and understanding the drivers of this variance, policymakers can better manage the financial dynamics of health insurance markets and thereby promote a more efficient, high-quality, and affordable healthcare system for all, for now, and in the future.

References

- Achmea. (2022). *Achmea zet reserves in om stijging zorgpremie 2023 te beperken*. Retrieved from <https://nieuws.achmea.nl/achmea-zet-reserves-in-om-stijging-zorgpremie-2023-te-beperken/> (Accessed: August 7, 2024)
- Almansour, B. Y., Elkrghli, S., & Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics & Finance*, 11(2). Retrieved from <https://doi.org/10.1080/23322039.2023.2239032>
- Back, K. E. (2017). Utility & risk aversion. In *Asset pricing and portfolio choice theory*. Oxford University Press. Retrieved from <https://doi.org/10.1093/acprof:oso/9780190241148.001.0001>
- Bodie, Z., Kane, A., Marcus, A. J., Perrakis, S., Ryan, P. J., & Switzer, L. (2014). *Investments*. McGraw-Hill Education. Retrieved from <https://books.google.nl/books?id=0eWtoAEACAAJ>
- de Vries, T. (2022). *Identifying under- and overcompensated groups in the dutch risk equalization model using stacking as a benchmark-model* (Master's Thesis, Erasmus University Rotterdam, Erasmus School of Economics). Retrieved from <https://thesis.eur.nl/pub/65806>
- Douven, R., & Mannaerts, H. (2008). Doelmatige zorg versus risicoselectie. *Economisch Statistische Berichten*, 93, 132–135. Retrieved from <https://pure.eur.nl/en/publications/doelmatige-zorg-versus-risicoselectie> (English translation: Efficiency in the delivery of care versus risk selection)
- Eeckhoudt, L., & Schlesinger, H. (2013). Higher-order risk attitudes. In G. Dionne (Ed.), *Handbook of insurance* (pp. 41–57). Springer New York. Retrieved from https://doi.org/10.1007/978-1-4614-0155-1_2
- Equalis. (2023). *Complexiteit in de uitvoering van de risicoverevening*. Retrieved from <https://www.zorginstituutnederland.nl/binaries/zinl/documenten/rapport/2023/10/06/onderzoek-complexiteit-risicovereveningsmodel/Onderzoeksrapport+Complexiteit+van+het+risicovereveningsmodel.pdf> (Contributors: G. Hamstra, Saskia Borg, Patric Suurenbroek, Piet Stam)
- Erasmus School of Health Policy & Management (ESHPM). (2020a). *Wor 1002: Onderzoek risicoverevening 2021 berekening normbedragen*. <https://www.zorginstituutnederland.nl/binaries/zinl/documenten/publicatie/2020/10/16/wor-1002-eindrapportage-normbedragen-2021/WOR+1002+Eindrapportage+Normbedragen+2021.PDF>
- Erasmus School of Health Policy & Management (ESHPM). (2020b). *Wor 988: Grootonderhoud dkg's t.b.v. somatisch model 2021: Onderzoek ten behoeve van het ministerie van volksgezondheid, welzijn en sport*. <https://open.overheid.nl/repository/ronl-541452cb-600a-4ada>

9847-682de4317410/1/pdf/WOR

- Erasmus School of Health Policy & Management (ESHPM). (2021). *Wor 1054: Onderzoek risicoverevening 2022 berekening normbedragen*. <https://www.zorginstituutnederland.nl/publicaties/publicatie/2021/10/15/wor-1054-eindrapportage-normbedragen-2022>.
- Erasmus School of Health Policy & Management (ESHPM). (2022). *Wor 1100: Onderzoek risicoverevening 2023 berekening normbedragen*. <https://www.zorginstituutnederland.nl/publicaties/publicatie/2022/09/30/wor-1110-definitieve-rapportage-normbedragen-rv2023>.
- Erasmus School of Health Policy & Management (ESHPM). (2023). *Onderzoek risicoverevening 2024: Overall toets*. <https://open.overheid.nl/documenten/452fcff4-9e7f-4faa-aa57-64fd4e06c9ab/file>. (Eindrapportage, 3 oktober 2023)
- European Parliament and Council of the European Union. (2009). *Directive 2009/138/ec of the european parliament and of the council of 25 november 2009 on the taking-up and pursuit of the business of insurance and reinsurance (solvency ii)*. <https://eur-lex.europa.eu/legal-content/en/ALL/?uri=CELEX%3A32009L0138>. (Accessed: 15 May 2024)
- Folland, S., Goodman, A. C., & Stano, M. (2012). *The economics of health and health care: Pearson new international edition* (7th ed.). Routledge. doi: 10.4324/9781315510736
- Francis, A., Harhay, M., Ong, A., et al. (2024). Chronic kidney disease and the global public health agenda: an international consensus. *Nature Reviews Nephrology*, 20, 473–485. Retrieved from <https://doi.org/10.1038/s41581-024-00820-6>
- Gai, P., & Vause, N. (2005). Measuring investors' risk appetite. *Bank of England Working Paper Series*(283). Retrieved from <http://dx.doi.org/10.2139/ssrn.872695>
- Geruso, M., & Layton, T. J. (2017). Selection in health insurance markets and its policy remedies. *The Journal of Economic Perspectives*, 31(4), 23–50. Retrieved from <https://doi.org/10.1257/jep.31.4.23>
- Kumar, M., Dev, S., Khalid, M. U., Siddenth, S. M., Noman, M., John, C., ... Mohamad, T. (2023). The bidirectional link between diabetes and kidney disease: Mechanisms and management. *Cureus*, 15(9), e45615. Retrieved from <https://doi.org/10.7759/cureus.45615>
- Mangram, M. E. (2013). A simplified perspective of the markowitz portfolio theory. *Global Journal of Business Research*, 7(1), 59–70. Retrieved from <https://ssrn.com/abstract=2147880>
- Nederlandse Zorgautoriteit. (2016). *Risicoselectie en risicosolidariteit zorgverzekeringsmarkt: Kwalitatief onderzoek 2016*. Retrieved from <https://zoek.officielebekendmakingen.nl/blg-784104.pdf> (Rapport)
- Nederlandse Zorgautoriteit. (2019). *Monitor zorgverzekeringen*. <https://puc.overheid.nl/nza>. (PUC 289640 22/1)
- Newhouse, J. P. (1996). Reimbursing health plans and health providers: Efficiency in production versus selection. *Journal of Economic Literature*, 34(3), 1236–1263. Retrieved from <http://www.jstor.org/stable/2729501>
- Nierstichting. (n.d.). *Feiten en cijfers over nierziekten*. <https://nierstichting.nl/leven-met-een-nierziekte/feiten-en-cijfers/>. (Accessed: August 3, 2024)

-
- Oskam, M., van Kleef, R. C., & Douven, R. (2024). Heteroscedasticity of residual spending after risk equalization: A potential source of selection incentives in health insurance markets with premium regulation. *European Journal of Health Economics*, *25*, 379–396. Retrieved from <https://doi.org/10.1007/s10198-023-01592-9>
- Otter, B. (2012). *The dutch risk equalization model and predictable profits: Are students and higher educated individuals profitable? risk selection in a regulated health insurance market review* (Master's thesis, Erasmus University Rotterdam). Retrieved from <https://thesis.eur.nl/pub/12755>
- Rijksoverheid. (2022). *Onderzoek risicoverevening 2023: Berekening normbedragen*. Retrieved from <https://www.rijksoverheid.nl/binaries/rijksoverheid/documenten/rapporten/2022/09/30/onderzoek-risicoverevening-2023-berekening-normbedragen/WOR+1110+-+Definitieve+rapportage+Normbedragen+RV2023.pdf> (Accessed: August 7, 2024)
- Rijksoverheid. (2024). *Premie zorgverzekering*. Retrieved from <https://www.rijksoverheid.nl/onderwerpen/zorgverzekering/vraag-en-antwoord/premie-zorgverzekering> (Accessed: August 7, 2024)
- Ross, S. A. (1981). Some stronger measures of risk aversion in the small and the large with applications. *Econometrica*, *49*(3), 621–638. Retrieved 2024-05-01, from <http://www.jstor.org/stable/1911515>
- van de Ven, W., Hamstra, G., van Kleef, R. C., et al. (2023). The goal of risk equalization in regulated competitive health insurance markets. *European Journal of Health Economics*, *24*, 111–123. Retrieved from <https://doi.org/10.1007/s10198-022-01457-7>
- van Kleef, R., & van Vliet, R. (2012). Improving risk equalization using multiple-year high cost as a health indicator. *Medical Care*, *50*(2), 140–144. Retrieved from <https://doi.org/10.1097/MLR.0b013e318234dbcd> doi: 10.1097/MLR.0b013e318234dbcd
- van Kleef, R., van Vliet, R., & van de Ven, W. (2012). Risicoverevening tussen zorgverzekeraars: Kwantificering modelverbeteringen 1993-2011. *Tijdschrift voor Gezondheidswetenschappen*, *90*, 312–326. Retrieved from <https://doi.org/10.1007/s12508-012-0110-0>
- van Kleef, R., van Vliet, R., & van de Ven, W. (2015). Een innovatieve schattingsmethode voor de risicoverevening: Verkennend onderzoek naar mogelijkheden en effecten van ‘constrained regression’. *Instituut Beleid en Management Gezondheidszorg (iBMG), Erasmus Universiteit Rotterdam*. Retrieved from https://www.eur.nl/sites/corporate/files/Eindrapport_Constrained_Regression_-_01jun15_0.pdf
- van Kleef, R. C., Eijkenaar, F., van Vliet, R., & van de Ven, W. P. M. M. (2018). Health plan payment in the netherlands. In T. G. McGuire & R. C. van Kleef (Eds.), *Risk adjustment, risk sharing and premium regulation in health insurance markets* (pp. 397–429). Academic Press. doi: 10.1016/B978-0-12-811325-7.00014-2
- van Kleef, R. C., McGuire, T. G., van Vliet, R. C., & van de Ven, W. P. (2017, December). Improving risk equalization with constrained regression. *The European Journal of Health Economics*, *18*(9), 1137–1156. Retrieved from <https://doi.org/10.1007/s10198-016-0859-1>
- van Kleef, R. C., Schut, F. T., & van de Ven, W. P. (2018). Premium regulation, risk equalization,

-
- risk sharing, and subsidies: Effects on affordability and efficiency. In T. G. McGuire & R. C. van Kleef (Eds.), *Risk adjustment, risk sharing and premium regulation in health insurance markets* (pp. 21–54). Academic Press. Retrieved from <https://www.sciencedirect.com/science/article/pii/B9780128113257000026> doi: 10.1016/B978-0-12-811325-7.00002-6
- van Kleef, R. C., van de Ven, W. P., & van Vliet, R. C. (2013, December). Risk selection in a regulated health insurance market: a review of the concept, possibilities and effects. *Expert Review of Pharmacoeconomics & Outcomes Research*, 13(6), 743-752. Retrieved from <https://doi.org/10.1586/14737167.2013.841546>
- van Kleef, R. C., van Vliet, R., Oskam, M., & Panturu, A. (2023). *Constrained regression als schattingsmethode voor de risicoverevening: mogelijkheden, effecten en afwegingen*.
- Vervloet, M. G., de Jong, H. J., Pander, J., & Overbeek, J. A. (2023). Prevalence of chronic kidney disease in the netherlands and its cardiovascular and renal complications. *BMC Nephrology*, 24(1), 337. doi: <https://doi.org/10.1186/s12882-023-03384-y>
- Withagen-Koster, A., van Kleef, R., & Eijkenaar, F. (2018). Examining unpriced risk heterogeneity in the dutch health insurance market. *The European Journal of Health Economics*, 19, 1351–1363. Retrieved from <https://doi.org/10.1007/s10198-018-0979-x> doi: 10.1007/s10198-018-0979-x
- Withagen-Koster, A. A., van Kleef, R. C., & Eijkenaar, F. (2023). Predictable profits and losses in a health insurance market with risk equalization: A multiple-contract period perspective. *Health Policy*, 131, 104763. Retrieved from <https://doi.org/10.1016/j.healthpol.2023.104763>
- World Health Organization. (2024). *Atc/DDD toolkit: Methodology*. Retrieved from <https://www.who.int/tools/atc-ddd-toolkit/methodology> (Accessed: August 7, 2024)
- Zorginstituut Nederland. (n.d.). *Zorgverzekeringswet*. <https://www.zorginstituutnederland.nl/Verzekerde+zorg/zvw-algemeen-hoe-werkt-de-zorgverzekeringswet>. (Accessed: 24 July 2024)
- Zorginstituut Nederland. (2020a). *Referentiebestand fkg 2021*. <https://www.zorginstituutnederland.nl/binaries/zinl/documenten/publicatie/2020/10/16/referentiebestand-fkgs-2021/Referentiebestand+FKGs+2021.ods#:~:text=Zorginstituut%20Nederland%20hanteert%20een%20drempel,anders%20dan%20'geen%20FKG'>. (Accessed: 20 July 2024)
- Zorginstituut Nederland. (2020b). *Verantwoording verzekerdenraming 2021*. <https://www.zorginstituutnederland.nl/publicaties/publicatie/2020/10/06/verantwoording-verzekerdenraming-2021>. (Accessed: 20 July 2024)
- Zorginstituut Nederland. (2021a). *Referentiebestand fkg 2022*. https://www.zorginstituutnederland.nl/publicaties/publicatie/2021/10/15/referentiebestand-fkg_c-2022. (Accessed: 20 July 2024)
- Zorginstituut Nederland. (2021b). *Verantwoording verzekerdenraming 2022*. <https://www.zorginstituutnederland.nl/publicaties/publicatie/2022/09/20/verantwoording-verzekerdenraming-2022>. (Accessed: 20 July 2024)
- Zorginstituut Nederland. (2022a). *Referentiebestand fkg 2023*. <https://www>

-
- .zorginstituutnederland.nl/publicaties/publicatie/2022/10/13/bijlage-2-referentiebestand-fkg_c-2023. (Accessed: 20 July 2024)
- Zorginstituut Nederland. (2022b). *Regeling risicoverevening 2023*. <https://www.zorginstituutnederland.nl/publicaties/publicatie/2022/10/13/concept-regeling-risicoverevening-2023>.
- Zorginstituut Nederland. (2022c). *Verantwoording verzekerenraming 2023*. <https://www.zorginstituutnederland.nl/publicaties/publicatie/2022/09/20/verantwoording-verzekerenraming-2023>. (Accessed: 15 July 2024)
- Zorginstituut Nederland. (2024a). *Basispakket zorgverzekeringswet (zvw)*. Retrieved from <https://www.zorginstituutnederland.nl/Verzekerde+zorg/b/basispakket-zorgverzekeringswet-zvw> (Accessed: August 7, 2024)
- Zorginstituut Nederland. (2024b). *Zorgkosten basispakket en langdurige zorg fors hoger in 2023*. Retrieved from <https://www.zorginstituutnederland.nl/actueel/nieuws/2024/01/17/zorgkosten-basispakket-en-langdurige-zorg-fors-hoger-in-2023> (Accessed: August 7, 2024)

Appendix A: Simplified example of compensation on an individual level

This paragraph describes a simplified example of how the Dutch somatic model determines the compensation that a health insurer receives for a certain individual.

Suppose, a health insurer has a policyholder who is 25 years old and lives in Rotterdam, Blijdorp. Next to her studies, she works part-time at the university. Her income and socioeconomic status are therefore low. She lives together with roommates she met in university. This is considered to be living on her own as she has no direct financial link to her roommates. She is relatively healthy but suffers from colitis ulcerosa. According to the somatic healthcare model of 2023 (WOR 1110), her estimated average somatic healthcare expenditure for the year 2023 equals:

Estimated average somatic healthcare expenditure in 2023 = €2559,72 (female, 25 years old) + €1374,83 (colitis ulcerosa) - €1486,63 (no other morbidity-based risk adjuster classification) - €62,11 (student, 25 years old) - €5,48 (region) - €13,17 (low socioeconomic status, 25 years old) + €48,91 (single-person household) = €2416,07.

She pays a yearly premium of €1650²⁹ to her health insurer. If we disregard the average costs for the mandatory deductible and the mental healthcare expenditures, the total compensation that a health insurer receives for this specific policyholder is equal to: €2416.07 - €1650 = €766.07 per year

²⁹ Average nominal premium in 2023 (Rijksoverheid, 2024)

Appendix B: The number of risk adjusters & risk classes 2021-2023

Overview of risk adjusters and the number of risk classes per risk adjusters used for the Dutch somatic ex-ante risk equalization models in the period 2021-2023.

Riskadjuster	Description	2021	2022	2023
Gender*Age	Interaction between age and gender	42	42	42
PCG	Pharmaceutical cost groups	39	43	48
DCG	Diagnostic cost groups	27	27	27
DMECG	Durable Medical equipment cost groups	15	15	15
SoI*Age	Source of income	36	36	36
Region	Region based on postal address	10	10	10
SES*Age	Social-economic status	12	12	12
PPA*Age	Persons per address	13	13	13
MYHC	Multiple-year high cost groups	9	9	9
PDCG	Physiotherapy diagnosis cost groups	5	5	5
PSHC	Prior spending on home care	10	10	10
HSM	Historical somatic morbidity	-	2	2
MYPC	Multi-year pharmaceutical costs	-	2	2
IPB	Indication Pregnancy and Birth	-	-	2
Total		218	226	233

Appendix C: Profit margins of Dutch health insurers 2012-2022

	Profit margin 2022	Profit margin 2021	Profit margin 2020	Profit margin 2019	Profit margin 2018	Profit margin 2017	Profit margin 2016	Profit margin 2015	Profit margin 2014	Profit margin 2013	Profit margin 2012	Average profit margins 2022-2012
ZILVEREN KRUIS ZORGVERZEKERINGEN NV	n.a.	-0,68	0,52	0,18	0,53	-1,01	-8,55	5,30	10,93	n.a.	5,05	1,362380952
VGZ ZORGVERZEKERAAAR NV	-1,47	0,28	-0,47	1,12	1,32	-0,73	-1,76	1,71	1,69	1,23	1,44	0,395505556
MENZIS ZORGVERZEKERAAAR N.V.	-2,23	-0,92	-1,01	1,76	0,56	1,21	-1,52	-1,12	4,36	2,14	2,54	0,524211111
NV UNIVE ZORG	n.a.	-0,47	1,01	-1,05	-0,90	-0,56	1,10	1,89	1,60	n.a.	1,70	0,479809524
OHRA ZORGVERZEKERINGEN NV	n.a.	2,39	2,28	2,46	-2,37	2,33	-3,21	4,34	3,61	n.a.	1,83	1,517369048
OWM ZORGVERZEKERAAAR ZORG EN ZEKERHEID UA	n.a.	-2,27	0,70	2,37	1,76	-0,25	-1,05	1,40	4,30	n.a.	2,87	1,092642857
DE FRIESLAND ZORGVERZEKERAAAR N.V.	n.a.	-3,91	0,67	-0,48	1,90	-0,03	-0,04	1,52	4,39	n.a.	3,81	0,871047619
ASR BASIC ZIEKTEKOSTENVERZEKERINGEN NV	n.a.	2,12	0,50	0,80	-0,21	-0,48	3,99	0,91	n.a.	n.a.	1,39	1,126178571
ONVZ ZIEKTEKOSTENVERZEKERAAAR NV	-3,75	-2,06	1,91	0,40	-1,69	-3,77	-1,18	-0,57	3,95	1,32	1,74	-0,337277778
INTERPOLIS ZORGVERZEKERINGEN NV	n.a.	-0,40	0,84	-2,16	1,50	3,29	-4,37	6,89	6,04	n.a.	5,23	1,871535714
ENO ZORGVERZEKERAAAR NV	n.a.	-0,84	0,30	1,98	6,89	-1,37	5,28	-0,77	2,50	n.a.	2,80	1,863119048
STAD HOLLAND ZORGVERZEKERAAAR OWM UA	n.a.	1,20	3,52	2,60	-1,62	2,93	-8,50	9,44	0,76	n.a.	1,17	1,277964286
DSW ZIEKTEKOSTENVERZEKERINGEN NV	n.a.	4,91	4,05	4,02	-2,20	-0,31	-0,54	-0,55	4,81	n.a.	-0,13	1,563011905
ACHMEA ZORGVERZEKERINGEN N.V.	n.a.											
NATIONALE-NEDERLANDEN VERZEKEREN SERVICES B.V.	n.a.											
ANDERSZORG	n.a.											
Aggregated	-2,483333333	-0,051	1,139076923	1,076692308	0,421076923	0,095538462	-1,565153846	2,337307692	4,078	1,56287963	2,418118926	1,046730647

Figure 1: Profit margins of Dutch health insurers 2012-2022 (Orbis, 2024)

Appendix D: Descriptive statistics of Residual spending in 2023

Table 1: Residual spending of risk classes for the risk adjuster "Gender*Age"

Risk Adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
Men	0 Years, born this year	42280.91	0.00	42513.03
Men	0 years, born last year	44267.27	0.00	12142.00
Men	1-4 Years	350950.81	0.00	7643.33
Men	5-9 Years	460139.60	0.00	5323.16
Men	10-14 Years	484052.35	0.00	5743.20
Men	15-17 Years	308164.82	0.00	6020.78
Men	18-24 Years	736942.83	0.00	4662.69
Men	25-29 Years	549395.52	0.00	3777.62
Men	30-34 Years	543208.85	0.00	3760.99
Men	35-39 Years	513183.24	0.00	3930.21
Men	40-44 Years	497410.76	0.00	4436.76
Men	45-49 Years	565243.67	0.00	5476.45
Men	50-54 Years	634041.27	0.00	6608.07
Men	55-59 Years	621313.31	0.00	7914.07
Men	60-64 Years	557285.36	0.00	9498.24
Men	65-69 Years	491522.92	0.00	10836.30
Men	70-74 Years	463223.47	0.00	12037.24
Men	75-79 Years	303475.19	0.00	12553.66
Men	80-84 Years	191732.25	0.00	12104.85
Men	85-89 Years	96255.99	0.00	12210.32
Men	90+ Years	37396.91	0.00	12933.12
Women	0 Years, born this year	40067.32	0.00	39307.53
Women	0 years, born last year	42270.99	0.00	10545.38
Women	1-4 Years	333716.72	0.00	6717.88
Women	5-9 Years	437771.96	0.00	5001.82
Women	10-14 Years	460832.39	0.00	4204.92
Women	15-17 Years	293955.73	0.00	5236.69
Women	18-24 Years	712723.95	0.00	3639.32
Women	25-29 Years	541785.18	0.00	3701.60
Women	30-34 Years	540804.32	0.00	3827.75
Women	35-39 Years	515080.54	0.00	4203.28
Women	40-44 Years	506060.87	0.00	4636.95
Women	45-49 Years	577324.43	0.00	5204.05
Women	50-54 Years	635324.48	0.00	5787.92
Women	55-59 Years	623074.28	0.00	6507.05

Continued on next page

Table 1 – continued from previous page

Risk Adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
Women	60-64 Years	563636.02	0.00	7387.18
Women	65-69 Years	503058.23	0.00	8380.14
Women	70-74 Years	485550.52	0.00	9109.46
Women	75-79 Years	340532.50	0.00	9604.72
Women	80-84 Years	249392.18	0.00	10097.23
Women	85-89 Years	160303.70	0.00	10830.00
Women	90+ Years	93475.92	0.00	11634.14

Table 2: Residual spending of risk classes for the risk adjuster "PCGs"

Risk Adj.	Risk class	Insured yrs(#)	Residual spending (€)	
			Mean	Std. dev.
PCG	No PCG	12673258.36	17.83	5734.04
PCG	COPD/Asthma: Medication	172822.10	17.83	9279.64
PCG	Diabetes: Insulin	6845.30	17.83	19727.13
PCG	Diabetes: Oral Medication	180488.18	17.83	11341.04
PCG	CVRM: Light Medication	1138338.33	17.83	8996.91
PCG	CVRM: Heavy Medication	740834.23	17.83	11168.60
PCG	Thyroid Disorders	333862.65	17.83	9258.22
PCG	Glaucoma	188428.46	17.83	11229.95
PCG	Depression	484505.88	17.83	8904.32
PCG	Psychosis	103450.95	17.83	9012.37
PCG	Epilepsy	88966.95	17.83	12779.83
PCG	Chronic Anticoagulation	329836.67	17.83	12567.04
PCG	Transplants	20472.35	17.83	25484.51
PCG	Parkinson's Disease	29141.18	17.83	15046.07
PCG	Heart Diseases: Other	300285.34	17.83	16785.83
PCG	Chronic Pain Excl. Opioids	170315.17	17.83	11107.53
PCG	Neuropathic Pain	73525.27	17.83	15344.86
PCG	Diabetes Type II W/o Hypertension	99092.98	17.83	10226.04
PCG	Diabetes Type II With Hypertension	242745.39	17.83	11764.82
PCG	Diabetes Type I W/o Hypertension	85707.15	17.83	10822.56
PCG	Diabetes Type I With Hypertension	161724.10	17.83	15742.03
PCG	Cystic Fibrosis/Pancreatic Enzymes	12646.84	17.83	21727.32
PCG	Growth Disorders	2890.51	17.83	26577.53
PCG	Brain/Spinal Cord Disorders: Other	77713.79	17.83	23544.66
PCG	Brain/Spinal Cord Disorders: MS	6591.90	17.83	9880.86

Continued on next page

Table 2 Continued from previous page

Risk Adj.	Risk class	Insured yrs(#)	Residual spending (€)	
			Mean	Std. dev.
PCG	HIV/AIDS	21927.31	17.83	9733.85
PCG	Psoriasis	25006.45	17.83	10183.25
PCG	Crohn's Disease/Ulcerative Colitis	67350.70	17.83	11333.42
PCG	Rheumatism	67350.70	17.83	10705.18
PCG	Autoimmune Diseases	58376.57	17.83	11158.64
PCG	Kidney Diseases	5316.39	17.83	34636.14
PCG	Acromegaly	2505.61	17.83	23239.67
PCG	Immunoglobulin	3362.64	17.83	49243.83
PCG	Asthma	371893.78	17.83	9361.21
PCG	COPD/Severe Asthma	253983.33	17.83	14394.14
PCG	COPD/Severe Asthma add-on	3330.55	17.83	15152.05
PCG	Hormone-Sensitive Tumors	56839.81	17.83	12386.36
PCG	Cancer	10041.82	17.83	11443.87
PCG	Cancer add-on	61442.54	17.83	37613.77
PCG	Pulmonary Arterial Hypertension	1708.05	17.83	40262.68
PCG	Macular Degeneration	44788.89	17.83	13306.69
PCG	Hypercholesterolemia	15242.07	17.83	11686.18
PCG	Heart Diseases: Antiarrhythmics	15242.07	17.83	10396.78
PCG	Addiction Excluding Nicotine	17740.52	17.83	11268.65
PCG	Extremely High Costs 1	1071.44	17.83	57623.89
PCG	Extremely High Costs 2	290.69	17.83	127720.14
PCG	Extremely High Costs 3	163.40	17.83	196720.11
PCG	Extremely High Costs 4	37.41	17.83	398310.53

Table 3: Residual spending of risk classes for the risk adjuster "DCGs"

Risk Adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
DCG	0	15109629.86	14.59	5721.68
DCG	1	514924.19	166.53	11865.37
DCG	2	459269.58	-4.18	13246.23
DCG	3	553993.91	-27.81	13305.39
DCG	4	202841.39	-4.04	17400.63
DCG	5	295754.67	-116.01	18281.14
DCG	6	139787.70	2.54	19428.32
DCG	7	95242.41	-94.46	22251.21
DCG	8	18334.69	28.61	28161.82

Continued on next page

Table 3 Continued from previous page

Risk Adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
DCG	9	28915.08	33.25	27406.67
DCG	10	16769.49	-12.59	27301.78
DCG	11	9292.65	7.53	24316.00
DCG	12	88347.92	54.27	31845.91
DCG	13	5638.16	-15.27	31926.82
DCG	14	14023.13	12.98	39029.90
DCG	15	17095.48	16.46	34886.29
DCG	16	25621.86	-72.13	30700.25
DCG	17	4926.78	-31.84	53466.69
DCG	18	4926.78	14.59	25077.76
DCG	19	6292.19	14.59	45587.20
DCG	20	3772.60	14.59	37870.25
DCG	21	3473.80	14.59	32719.40
DCG	22	5264.67	39.75	32719.40
DCG	23	10921.05	10.20	32719.40
DCG	24	4873.87	11.99	59295.03
DCG	25	7475.20	13.64	39610.78
DCG	26	1071.63	14.59	86757.11

Table 4: Residual spending of risk classes for the risk adjuster "DMECGs"

Risk Adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
DMECG	No DMECG	16340642.96	3.61	6810.75
DMECG	CPAP equipment	189435.83	3.61	11449.39
DMECG	Therapeutic elastic stockings	301330.29	3.61	12998,16
DMECG	Stoma supplies	49459.86	3.61	18586.37
DMECG	Nebulizer	25923.23	3.61	27658.32
DMECG	Urine collection devices	93227.78	3.61	19633.13
DMECG	Injection strings excl. diabetes	58457.9	3.61	23942.7
DMECG	Oxygen equipment	26723.39	3.61	26295.82
DMECG	Nutritional aids	857.77	3.61	74052.51
DMECG	Mucus suction equipment	14462.87	3.61	47820,95
DMECG	Portable infusion pumps	11955.83	3.61	39360,75
DMECG	Compression aids	85683.37	3.61	17584.89
DMECG	Orthotics	68223.92	3.61	17063.81
DMECG	Leg prostheses	7022.56	3.61	18635.16
DMECG	Insulin pumps	26404.96	3.61	10215.08

Table 5: Residual spending of risk classes for the risk adjuster "SoI*Age"

Risk Adj.	Risk Class	Age Group	Insured years	Residual spending (€)	
				Mean	Std. dev.
SoI*Age		70+ years	2421338.63	0.00	10985.89
SoI*Age	Incapacitated ³⁰	0-17 jaar	31319.08	0.00	8674.19
SoI*Age	Incapacitated	18-34 jaar	2682.19	0.00	13960.57
SoI*Age	Incapacitated	35-44 jaar	12533.91	0.00	13736.52
SoI*Age	Incapacitated	45-54 jaar	29803.68	0.00	14158.11
SoI*Age	Incapacitated	55-64 jaar	67024.71	0.00	14103.60
SoI*Age	Incapacitated	65-69 jaar	27479.47	0.00	13930.21
SoI*Age	Part. incapacitated	0-17 jaar	207422.93	0.00	10528.12
SoI*Age	Part. incapacitated	18-34 jaar	129394.48	0.00	8772.32
SoI*Age	Part. incapacitated	35-44 jaar	99557.52	0.00	8303.73
SoI*Age	Part. incapacitated	45-54 jaar	151100.90	0.00	9123.90
SoI*Age	Part. incapacitated	55-64 jaar	218515.28	0.00	10263.08
SoI*Age	Part. incapacitated	65-69 jaar	133087.38	0.00	11731.00
SoI*Age	Social assistance	0-17 jaar	206862.57	0.00	9324.14
SoI*Age	Social assistance	18-34 jaar	113880.68	0.00	5803.28
SoI*Age	Social assistance	35-44 jaar	99844.33	0.00	5617.29
SoI*Age	Social assistance	45-54 jaar	125557.45	0.00	7311.49
SoI*Age	Social assistance	55-64 jaar	128714.88	0.00	9169.13
SoI*Age	Social assistance	65-69 jaar	46793.02	0.00	11015.33
SoI*Age	Students	0-17 jaar	25221.13	0.00	14367.99
SoI*Age	Students	18-34 jaar	618778.11	0.00	3337.94
SoI*Age	Self-employed	0-17 jaar	413856.25	0.00	8155.79
SoI*Age	Self-employed	18-34 jaar	291789.01	0.00	3060.79
SoI*Age	Self-employed	35-44 jaar	334728.51	0.00	3357.37
SoI*Age	Self-employed	45-54 jaar	272171.57	0.00	4559.24
SoI*Age	Self-employed	55-64 jaar	213872.04	0.00	6422.76
SoI*Age	Self-employed	65-69 jaar	54842.34	0.00	9039.29
SoI*Age	Highly educated	0-17 jaar	217391.72	0.00	10243.79
SoI*Age	Highly educated	18-34 jaar	629385.38	0.00	3285.93
SoI*Age	Highly educated	35-44 jaar	422851.24	0.00	3603.92
SoI*Age	Reference group	0-17 jaar	2196397.19	0.00	8361.74
SoI*Age	Reference group	18-34 jaar	1838950.80	0.00	3730.62
SoI*Age	Reference group	35-44 jaar	1062219.90	0.00	3887.68
SoI*Age	Reference group	45-54 jaar	1833300.25	0.00	5255.46
SoI*Age	Reference group	55-64 jaar	1737182.06	0.00	7211.30
SoI*Age	Reference group	65-69 jaar	732378.94	0.00	8993.69

³⁰Permanent and fully.

Table 6: Residual spending of risk classes for the risk adjuster "Region"

Risk adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
Region	1	1711800.57	0.00	7963.83
Region	2	1705299.44	0.00	7702.79
Region	3	1705891.41	0.00	7583.98
Region	4	1709283.94	0.00	7469.63
Region	5	1720543.69	0.00	7505.82
Region	6	1711258.58	0.00	7383.69
Region	7	1708533.01	0.00	7435.71
Region	8	1726826.11	0.00	7356.75
Region	9	1718175.97	0.00	7255.48
Region	10	1730616.79	0.00	7123.17

Table 7: Residual spending of risk classes for the risk adjuster "SES*Age"

Risk adjuster	Riskclass	Agegroup	Insured years (#)	Residual spending (€)	
				Mean	Std. dev
SES*age	Very low	0-17	663,577.45	0.00	8,795.37
SES*age	Very low	18-69	2,355,005.74	0.00	6,588.33
SES*age	Very low	70+	596,006.02	0.00	10,818.04
SES*age	Low	0-17	658,674.57	0.00	9,380.43
SES*age	Low	18-69	2,268,314.39	0.00	6,370.59
SES*age	Low	70+	456,385.35	0.00	11,017.95
SES*age	Middle	0-17	988,137.83	0.00	9,006.80
SES*age	Middle	18-69	3,404,157.33	0.00	5,775.96
SES*age	Middle	70+	684,487.90	0.00	10,872.51
SES*age	High	0-17	988,081.02	0.00	7,984.72
SES*age	High	18-69	3,400,942.57	0.00	5,612.14
SES*age	High	70+	684,459.37	0.00	11,219.80

Table 8: Residual spending of risk classes for the risk adjuster "HHS*Age"

Risk adjuster	Risk class	Age Group	Insured years	Residual spending	
				Mean	Std. dev
HHS*Age		0-17	3,298,470.87	0.00	8,748.41
HHS*Age	Long term care (perm)	18-69	74,472.38	0.00	7,455.06
HHS*Age	Long term care (perm)	70-79	24,225.52	0.00	7,528.12
HHS*Age	Long term care (perm)	80+	79,386.69	0.00	6,157.13
HHS*Age	Long term care (entering)	18-69	5,941.45	0.00	29,937.30
HHS*Age	Long term care (entering)	70-79	8,181.58	0.00	22,293.58

Continued on next page

Risk adjuster	Risk class	Age Group	Insured years	Residual spending	
				Mean	Std. dev
HHS*Age	Long term care (entering)	80+	26,888.16	0.00	17,107.44
HHS*Age	Single person household	18-69	1,597,389.15	0.00	7,090.77
HHS*Age	Single person household	70-79	398,440.71	0.00	10,802.05
HHS*Age	Single person household	80+	340,175.25	0.00	11,674.69
HHS*Age	Other	18-69	9,750,617.04	0.00	5,774.98
HHS*Age	Other	70-79	1,161,933.87	0.00	10,767.78
HHS*Age	Other	80+	382,106.86	0.00	11,247.22

Table 9: Residual spending of risk classes for the risk adjuster "MYHC"

Risk adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
MYHC	0	9,478,739.71	0.00	5,391.71
MYHC	1	6,641,924.49	0.00	7,445.88
MYHC	2	167,402.40	0.00	17,997.08
MYHC	3	399,672.08	0.00	13,071.05
MYHC	4	191,302.89	0.00	15,144.27
MYHC	5	147,038.48	0.00	17,315.75
MYHC	6	90,678.43	0.00	21,667.54
MYHC	7	20,659.55	0.00	33,885.22
MYHC	8	10,811.50	0.00	60,137.10

Table 10: Residual spending of risk classes for the risk adjuster "PDCG"

Risk adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
PDCG	0	16,645,526.99	0.00	7,209.99
PDCG	1	277,050.78	0.00	10,300.2
PDCG	2	223,023.03	0.00	16,646.78
PDCG	3	1,991.02	0.00	33,309.63
PDCG	4	637.71	0.00	38,398.56

Table 11: Residual spending of risk classes for the risk adjuster "PSHC"

Risk adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
PSHC	1	16,706,455.60	0.00	6,869.77
PSHC	2	72,913.51	0.00	16,336.45
PSHC	3	69,988.23	0.00	17,641.63

Continued on next page

Table 11 continued from previous page

Risk adjuster	Risk class	Insured years (#)	Mean	Std. dev.
PSHC	4	64,233.34	0.00	19,021.43
PSHC	5	58,449.60	0.00	18,906.16
PSHC	6	56,372.46	0.00	19,490.96
PSHC	7	57,930.52	0.00	19,066.32
PSHC	8	29,991.62	0.00	19,012.74
PSHC	9	30,411.05	0.00	25,590.77
PSHC	10	1,483.58	0.00	92,186.15

Table 12: Residual spending of risk classes for the risk adjuster "HSM"

Risk adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
HSM	0	9,291,377.19	0.00	6,269.41
HSM	1	7,856,852.34	0.00	8,698.21

Table 13: Residual spending of risk classes for the risk adjuster "MYPC"

Risk adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	Std. dev.
MYPC	0	11,818,083.09	0.00	5,564.21
MYPC	1	5,330,146.43	0.00	10,554.37

Table 14: Residual spending of risk classes for the risk adjuster "IPB"

Risk adjuster	Risk class	Insured years (#)	Residual spending (€)	
			Mean	std. dev.
IPB	0	16,990,379.82	0.00	7,505.21
IPB	1	157,849.70	0.00	4,062.33

**Appendix E: Risk premia required for all risk classes in 2023
(absolute standard deviations)**

**Appendix F: Risk premia required for all risk classes in 2023
(adjusted standard deviations)**

Risk adjuster variables	Risk classes	Risk premium (a = 0.01)	Risk premium (a = 0.02)	Risk premium (a = 0.09)	Risk premium (a = 0.10)	Risk premium (a = 0.10)	% change in compensation (a=0.01)	% change in compensation (a=0.02)	% change in compensation (a=0.09)	% change in compensation (a=0.10)
Pharmacy-based Cost Groups	Pharmacy-based Cost Groups	1,457.54	1,457.54	1,457.54	1,457.54	1,457.54	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG2	2.53	2,911.51	1,311.79	22.80	0.01	0.07%	0.14%	0.00%	0.71%
Age*Gender	AG3	0.00	5.07	0.01	0.01	0.01	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG4	(0.05)	(0.09)	(0.42)	(0.47)	(0.05)	0.00%	0.00%	-0.02%	-0.02%
Age*Gender	AG5	(0.03)	(0.06)	(0.26)	(0.29)	(0.03)	0.00%	0.00%	-0.01%	-0.01%
Age*Gender	AG6	(0.05)	(0.10)	(0.46)	(0.51)	(0.05)	0.00%	0.00%	-0.02%	-0.02%
Age*Gender	AG7	(0.05)	(0.10)	(0.46)	(0.51)	(0.05)	0.00%	0.00%	-0.02%	-0.02%
Age*Gender	AG8	(0.12)	(0.24)	(1.08)	(1.20)	(0.12)	-0.01%	-0.01%	-0.05%	-0.05%
Age*Gender	AG9	(0.12)	(0.24)	(1.08)	(1.22)	(0.12)	-0.01%	-0.01%	-0.05%	-0.05%
Age*Gender	AG10	(0.12)	(0.24)	(1.08)	(1.22)	(0.12)	-0.01%	-0.01%	-0.05%	-0.05%
Age*Gender	AG11	(0.09)	(0.18)	(0.80)	(0.88)	(0.09)	-0.01%	-0.01%	-0.04%	-0.04%
Age*Gender	AG12	(0.09)	(0.18)	(0.80)	(0.88)	(0.09)	-0.01%	-0.01%	-0.04%	-0.04%
Age*Gender	AG13	(0.01)	(0.01)	(0.05)	(0.05)	(0.01)	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG14	0.00	0.00	0.02	0.02	0.00	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG15	0.04	0.08	0.35	0.39	0.04	0.00%	0.00%	0.01%	0.01%
Age*Gender	AG16	0.12	0.24	1.08	1.20	0.12	0.00%	0.00%	0.03%	0.04%
Age*Gender	AG17	0.12	0.24	1.08	1.20	0.12	0.00%	0.00%	0.03%	0.04%
Age*Gender	AG18	0.44	0.87	3.93	4.37	0.44	0.02%	0.02%	0.09%	0.10%
Age*Gender	AG19	0.58	1.15	5.18	5.76	0.58	0.01%	0.01%	0.13%	0.14%
Age*Gender	AG20	1.20	2.40	10.79	11.99	1.20	0.02%	0.02%	0.21%	0.24%
Age*Gender	AG21	4.08	8.17	36.76	40.85	4.08	0.07%	0.14%	0.64%	0.71%
Age*Gender	AG22	127.09	2,541.81	1,143.50	20,720.02	127.09	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG23	1.74	3.47	14.56	16.19	1.74	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG24	(0.01)	(0.01)	(0.06)	(0.07)	(0.01)	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG25	(0.07)	(0.13)	(0.59)	(0.66)	(0.07)	-0.01%	-0.01%	-0.03%	-0.04%
Age*Gender	AG26	(0.11)	(0.22)	(1.11)	(1.11)	(0.11)	0.00%	0.00%	-0.04%	-0.04%
Age*Gender	AG27	(0.08)	(0.16)	(0.72)	(0.80)	(0.08)	0.00%	0.00%	-0.03%	-0.03%
Age*Gender	AG28	(0.13)	(0.26)	(1.27)	(1.27)	(0.13)	0.00%	0.00%	-0.04%	-0.04%
Age*Gender	AG29	(0.13)	(0.26)	(1.27)	(1.27)	(0.13)	0.00%	0.00%	-0.04%	-0.04%
Age*Gender	AG30	(0.12)	(0.24)	(1.07)	(1.18)	(0.12)	-0.01%	-0.01%	-0.05%	-0.05%
Age*Gender	AG31	(0.10)	(0.20)	(0.90)	(1.00)	(0.10)	-0.01%	-0.01%	-0.04%	-0.04%
Age*Gender	AG32	(0.08)	(0.15)	(0.76)	(0.88)	(0.08)	0.00%	0.00%	-0.03%	-0.03%
Age*Gender	AG33	(0.08)	(0.15)	(0.76)	(0.88)	(0.08)	0.00%	0.00%	-0.03%	-0.03%
Age*Gender	AG34	(0.08)	(0.15)	(0.76)	(0.88)	(0.08)	0.00%	0.00%	-0.03%	-0.03%
Age*Gender	AG35	(0.01)	(0.01)	(0.06)	(0.06)	(0.01)	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG36	0.01	0.02	0.08	0.09	0.01	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG37	0.01	0.02	0.08	0.09	0.01	0.00%	0.00%	0.00%	0.00%
Age*Gender	AG38	0.03	0.06	0.27	0.30	0.03	0.00%	0.00%	0.01%	0.01%
Age*Gender	AG39	0.15	0.29	1.31	1.45	0.15	0.00%	0.00%	0.03%	0.04%
Age*Gender	AG40	0.37	0.73	3.29	3.66	0.37	0.01%	0.01%	0.07%	0.08%
Age*Gender	AG41	0.96	1.91	8.61	9.56	0.96	0.02%	0.02%	0.17%	0.19%
Age*Gender	AG42	0.96	1.91	8.61	9.56	0.96	0.02%	0.02%	0.17%	0.19%
Risk adjuster variables	Risk classes	Risk premium (a = 0.01)	Risk premium (a = 0.02)	Risk premium (a = 0.09)	Risk premium (a = 0.10)	Risk premium (a = 0.10)	% change in compensation (a=0.01)	% change in compensation (a=0.02)	% change in compensation (a=0.09)	% change in compensation (a=0.10)
Pharmacy-based Cost Groups	Pharmacy-based Cost Groups	6,937.37	6,937.37	6,937.37	6,937.37	6,937.37	0.00%	0.00%	0.00%	0.00%
Pharmacy-based Cost Groups	PCG10	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	0.00%	0.00%	0.00%	0.00%
Pharmacy-based Cost Groups	PCG11	110.89	221.78	998.02	1,108.91	110.89	0.70%	0.40%	5.78%	52.01%
Pharmacy-based Cost Groups	PCG12	0.43	0.86	3.86	4.29	0.43	0.09%	0.02%	0.17%	0.77%
Pharmacy-based Cost Groups	PCG13	0.01	0.02	0.10	0.11	0.01	0.05%	0.02%	0.21%	0.86%
Pharmacy-based Cost Groups	PCG14	0.19	0.39	1.96	2.13	0.19	0.05%	0.02%	0.45%	2.30%
Pharmacy-based Cost Groups	PCG15	0.39	0.78	3.49	3.88	0.39	0.45%	0.24%	1.44%	7.44%
Pharmacy-based Cost Groups	PCG16	0.02	0.05	0.23	0.23	0.02	0.04%	0.07%	0.32%	2.26%
Pharmacy-based Cost Groups	PCG17	0.12	0.25	1.12	1.25	0.12	0.08%	0.08%	0.38%	4.2%
Pharmacy-based Cost Groups	PCG18	1.62	3.25	14.61	16.23	1.62	0.43%	0.43%	3.88%	4.31%
Pharmacy-based Cost Groups	PCG19	79.83	159.65	798.25	878.13	79.83	0.61%	0.61%	5.41%	6.01%
Pharmacy-based Cost Groups	PCG20	100.2	200.3	918.43	1,002.16	100.2	3.88%	3.88%	33.88%	37.45%
Pharmacy-based Cost Groups	PCG21	1.47	2.93	13.19	14.65	1.47	0.55%	0.55%	4.70%	5.16%
Pharmacy-based Cost Groups	PCG22	0.40	0.80	3.62	4.02	0.40	0.08%	0.08%	0.77%	0.69%
Pharmacy-based Cost Groups	PCG23	4.29	8.57	38.58	42.86	4.29	0.27%	0.27%	2.42%	2.69%
Pharmacy-based Cost Groups	PCG24	0.39	0.78	3.52	3.91	0.39	0.04%	0.04%	0.39%	0.44%
Pharmacy-based Cost Groups	PCG25	0.68	1.36	6.13	6.81	0.68	0.04%	0.04%	0.32%	0.36%
Pharmacy-based Cost Groups	PCG26	2.15	4.30	19.34	21.49	2.15	0.08%	0.08%	0.76%	0.84%
Pharmacy-based Cost Groups	PCG27	81.09	162.18	729.82	810.91	81.09	11.07%	11.07%	99.66%	110.73%
Pharmacy-based Cost Groups	PCG28	635.50	1,271.00	5,765.50	6,355.00	635.50	22.15%	22.15%	199.66%	221.5%
Pharmacy-based Cost Groups	PCG29	4.65	9.29	41.82	46.47	4.65	0.41%	0.41%	3.81%	4.07%
Pharmacy-based Cost Groups	PCG30	1.24	2.47	11.12	12.36	1.24	0.25%	0.25%	2.27%	2.52%
Pharmacy-based Cost Groups	PCG31	1.54	3.09	13.88	15.43	1.54	0.15%	0.15%	1.33%	1.48%
Pharmacy-based Cost Groups	PCG32	1.15	2.29	10.31	11.45	1.15	0.20%	0.20%	1.80%	2.00%
Pharmacy-based Cost Groups	PCG33	1.21	2.41	10.86	12.06	1.21	0.42%	0.42%	3.74%	4.07%
Pharmacy-based Cost Groups	PCG34	697.37	1,394.73	6,236.31	6,937.37	697.37	6.73%	13.46%	60.56%	67.29%
Pharmacy-based Cost Groups	PCG35	500.30	1,000.61	4,502.74	5,003.05	500.30	3.54%	7.08%	31.86%	35.40%
Pharmacy-based Cost Groups	PCG36	2,602.76	5,205.51	23,424.81	26,027.56	2,602.76	18.93%	37.85%	170.33%	189.25%
Pharmacy-based Cost Groups	PCG37	0.96	1.92	8.65	9.61	0.96	0.06%	0.06%	0.52%	0.57%
Pharmacy-based Cost Groups	PCG38	90.08	180.17	810.75	900.83	90.08	0.67%	1.33%	5.99%	6.66%
Pharmacy-based Cost Groups	PCG39	2.18	4.36	19.64	21.82	2.18	0.24%	0.48%	2.17%	2.42%
Pharmacy-based Cost Groups	PCG40	8.12	16.24	73.07	81.19	8.12	0.97%	0.97%	8.69%	9.65%
Pharmacy-based Cost Groups	PCG41	74.26	148.52	688.33	742.58	74.26	0.67%	0.67%	6.01%	6.68%
Pharmacy-based Cost Groups	PCG42	31.68	63.36	283.68	316.87	31.68	3.24%	3.24%	28.36%	31.68%
Pharmacy-based Cost Groups	PCG43	3.89	7.77	34.99	38.87	3.89	0.14%	0.14%	1.28%	1.38%
Pharmacy-based Cost Groups	PCG44	6.01	12.02	54.09	60.10	6.01	0.29%	0.58%	2.62%	2.91%
Pharmacy-based Cost Groups	PCG45	2.93	5.87	26.41	29.35	2.93	0.37%	0.75%	3.37%	3.75%
Pharmacy-based Cost Groups	PCG46	4.21	8.41	37.85	42.06	4.21	0.32%	0.64%	2.91%	3.24%
Pharmacy-based Cost Groups	PCG47	111.78	223.56	1,069.32	1,117.86	111.78	0.65%	1.30%	5.85%	6.46%
Pharmacy-based Cost Groups	PCG48	1,096.69	2,193.38	9,870.23	10,966.93	1,096.69	258.47%	516.94%	2,142.37%	2,316.73%
Pharmacy-based Cost Groups	PCG49	20.423,224.09	40,846,448.19	183,809,016.84	204,232,240.03	20,423,224.09	288.91%	577.81%	2,600.16%	2,889.06%
Risk adjuster variables	Risk classes	Risk premium (a = 0.01)	Risk premium (a = 0.02)	Risk premium (a = 0.09)	Risk premium (a = 0.10)	Risk premium (a = 0.10)	% change in compensation (a=0.01)	% change in compensation (a=0.02)	% change in compensation (a=0.09)	% change in compensation (a=0.10)
Diagnosis-based Cost Groups	DCG0	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	0.00%	0.00%	0.00%	0.00%
Diagnosis-based Cost Groups	DCG1	0.37	0.74	3.34	3.71	0.37	0.06%	0.09%	0.40%	0.44%
Diagnosis-based Cost Groups	DCG2	0.37	0.74	3.34	3.71	0.37	0.06%	0.09%	0.40%	0.44%

