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FACULTY OF SOCIAL SCIENCES

Institute of Economic Studies

Master's Thesis

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CHARLES UNIVERSITY

FACULTY OF SOCIAL SCIENCES

Institute of Economic Studies

Improvement of Risk Adjustment Model to Strengthen the Competition among Health Insurance Companies in Slovakia

Master's thesis

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Study programme: Ekonomie a finance

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Year of the defence: 2018

Declaration

1. I hereby declare that I have compiled this thesis using the listed literature and resources only.
2. I hereby declare that my thesis has not been used to gain any other academic title.
3. I fully agree to my work being used for study and scientific purposes.

In Prague on July 31, 2018 Bc. Barbora Chochláčová

References

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Abstract

As it is in many other sectors also in case of health insurance companies it is crucial to ensure sufficient competition what at the same reduces undesired adverse selection of enrollees. Therefore, the key is to have risk adjustment model that accurately captures future health care costs of individuals. PCG model currently used in Slovakia works apart from the simple demographic characteristics of the population as predictors also with chronic conditions. The main aim of the thesis is to compare this model in the form applied today with its modifications classifying more potentially chronic patients into the group, focusing on Hypercholesterolemia. We find a potential for improvement of the model in its adjusted versions bringing better results as from the profit/loss point of view so from R^2 increase. While the implementation of the suggested models into the system is not practically limited by the availability of the necessary information nor the time or financial demand.

Abstrakt

Tak ako v mnohých iných odvetviach, aj v prípade zdravotných poisťovní je zásadné, aby bola zaistená dostatočná konkurencieschopnosť a tým sa zároveň obmedzila nežiadúca selekcia poistencov. Kľúčové je preto, aby model kompenzácie rizika čo najpresnejšie zachytával budúce náklady jednotlivcov na zdravotnú starostlivosť. V súčasnosti sa na Slovensku používa tzv. PCG model, ktorý okrem najjednoduchších prediktorov na základe demografických charakteristík ľudí pracuje s chronickými ochoreniami. Cieľom práce je porovnať tento model v podobe, v akej je aplikovaný v súčasnosti s jeho obmenami zachycujúcimi väčšie množstvo potenciálne chronicky chorých, so zameraním na podskupinu hypercholesterolémie. Nachádzame potenciál pre zlepšenie modelu v jeho upravených verziách vykazujúcich lepšie výsledky ako z pohľadu zlepšenia hospodárskeho výsledku poisťovne, tak aj zvýšenia R^2. Implementácia navrhovaných modelov do systému pritom nie je prakticky limitovaná dostupnosťou potrebných informácií, časovou ani finančnou náročnosťou.

Keywords

PCG model, risk index, healthcare costs, risk adjustment, risk equalization, health insurance, Slovakia

Klíčová slova

PCG model, index rizika, náklady na zdravotnú starostlivosť, riziková úprava, vyrovnávanie rizík, zdravotné poistenie, Slovensko

Název práce

Možnosti změn modelu kompenzace struktury rizika pojistného kmene s cílem posílení konkurence zdravotních pojišťoven na Slovensku

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The words of gratitude go also to Mgr. Matej Poliak and Dôvera ZP, without which the thesis could not arise.

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Master's Thesis Proposal

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Proposed Topic:

Impact of Change in Risk Adjustment (Implementation of Pharmacy based Cost Group Model) on the Statutory Health Insurance in Czech Republic.

Motivation:

One of the most discussed social issues nowadays is indeed growth of chronical diseases as a result of increasing lifespan and aging population. Hence, it is now more than ever fundamental to bring changes into the health care systems that would follow the needs of society and improve our quality of life. Pharmacy based Cost Group Model (hereinafter referred to as "PCG model") is a methodology used for risk adjustment in health insurance integrated in several developed health care mechanisms around Europe including for instance Netherlands or from 2012 even Slovakia. It uses data concerning previous drug consumption of inhabitants as a predictor of costs on their health care. According to the amendment to the act about premiums for general health insurance, PCG model should be introduced also in Czech Republic from 1.1.2018. As this is indeed a vital change in health care system, I would like to investigate on concrete insurance company data what effects the model brings for both insurance companies as well as insurees.

There are several aims of new risk adjustment implementation. Most crucial and obvious one is to increase the fairness of premiums distribution among health care companies and subsequently to motivate them towards competition. To ensure that the distribution leads to these objectives, it has to be correctly and properly set up, i.e. effective insurers should have positive economic result for a given PCG group. Only then there is no need for cherry picking and insurers can be motivated to focus on more effective purchase of health care.

As long as it comes to motivation for insurers, the change should also optimize claim controlling activity – insurers should insist on Clinical practice guidelines, their stronger decision-making power in clinical procedures and gradual building of disease management programs. These programs should have a key impact on better health care quality for chronical patients.

Currently each insurer is trying to examine this impact and is searching for more and more relevant researches concluded on this topic. Recent publication dealing with similar topic was elaborated for example by Health Policy Institute on the calculation of risk indices using PCG and its impact on insurance companies (2014). Apart from this paper, I was also given an access to the relevant study concerning PCG model in Czech Republic by the author Tomáš Macháček, which is being prepared for the publishing.

To go even further in my thesis, I will try to propose potential changes or improvements to risk adjustment model which is about to be implemented in Czech Republic. My intention is to study economic results of the PCG groups and how they can be improved, as well as whether insurees are properly allocated to the groups, e.g. whether threshold of 180 defined daily doses for inclusion should not be modified.

Hypotheses:

1. Hypothesis #1: Current risk indices lead to negative economic results over the PCG groups.
2. Hypothesis #2: Main causalities are time delay of data and imprecise localization of the Dutch PCG model as a pattern.
3. Hypothesis #3: Defined daily dose of 180 is set up too high for some PCG groups.

Methodology:

Essential part of my thesis would be computation of risk indices applying combination of demographic indices used so far and indices according to cost groups in newly introduced PCG model. I would like to compare my computations of PCG indices with nationwide PCG indices and discuss potential motivation of risk selection from insurer's side. My intention should be to suggest appropriate modifications to avoid such a treatment.

Risk indices should be computed as a sum of costs indices relevant for demographic and PCG groups - via econometric analysis. As it is done in the paper by Health Policy Institute, appropriate methodology used should be weighted least squares regression.

Later on, to be able to design more relevant method for risk indices computation I would reckon based on data economic results of each of the PCG groups. The issue would be how to correctly count the economic results of each group, so that the outliers do not unbalance the whole group's costs. Possible solution that might be offered is cutting off the extreme-costs' patients.

Expected Contribution:

The results of my paper should contribute to the estimations currently provided for insurance companies considering potential results of new risk adjustment. However, as far as I am aware there are just few publications regarding PCG model in Czech Republic available to public. Therefore, my thesis should provide readers with all crucial details, specific transformation into practice using real and up-to-date data and even discussion about its pros and cons.

Above mentioned paper from Health Policy institute is dealing with older data (2009-2011) and has some shortcomings like PCG groups are used according to Slovak model, where different risk indices and fewer groups were applied or a person can be added at the most to one PCG group. Pattern for Czech Republic should be Dutch model and therefore I would like to deal with this type.

Outline:

1. Introduction into the topic and theoretical part: Motivation towards this topic and brief explanation of key concepts of risk adjustment. Previous technique used in Czech Republic, how PCG model works in other countries and what other types of models are used worldwide.
2. Previous studies concerning this topic: I would describe previous researches made on this topic, what is their contribution which can be used as a pattern in my thesis and what are their results. I would consider also what I would like to improve or what should be done beyond these studies.
3. Data: This part will be describing structure of data used for my computations, which I would not collect by myself but obtain from at least one insurance company – year of collection, their size and scope, specific meaning etc.
4. Methodology: What methods are used for index computations – suggested weighted least squares. How the economic result of each PCG group is defined including outlier adjustments. Dealing with time delay and Dutch pattern issues.
5. Results: I would comment on results from the empirical part of my paper and try to come up with my proposal for improvement.
6. Conclusion: Sum up my findings, how they could be used in real application.

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Acronyms

PCG	Pharmacy-based Cost Group
DDD	Defined Daily Doses
CDS	Chronic Disease Score
ATC	Anatomical Therapeutic Chemical
DCG	Diagnostic Cost Group
CZK	Czech Koruna
PDD	Prescribed Daily Doses
MAPE	Mean Absolute Prediction Error
MARE	Mean Absolute Relative Error
RE	Risk Equalization
OLS	Ordinary Least Square
RI	Risk Index
CHO	Hypercholesterolemia
HEM	Hemophilia

Introduction

There are almost 200 countries all around the world and each of them needs to somehow deal with the health care system setting. Unfortunately, majority of them, especially developing ones, do not have enough resources nor priority to establish the system in any way and so health care is provided just to those who directly pay for it. On the other side are nations with either one private insurer or insurance funds provided directly by the government or, so called *Bismarck model* (Physicians for a National Health Program nedatováno). Here, where the system is so that all the money gathered from the whole population in a form of premium should be distributed among several insurance companies, known as *sickness funds*, it is crucial to correctly set up the *risk adjustment* for prospective payments – a system for evaluating expected treatment costs for a specific subset of patients. People are divided into several groups according to observed factors which should the best capture future costs of health treatment. The funds are then allocated to insurers according to different weights of costs ascribed to each group.

The most crucial reason to develop a properly functioning risk adjustment system is to avoid adverse effects of selection (van de Ven et al. 2004). Systems lacking the effective compensation of costs for high-risk patients create an environment where insurance companies´ decisions are markedly driven by perverse incentives to select just the healthy ones and avoid individuals with chronic illnesses and others with higher demand for health care. Therefore, it is essential to find such a system, where sickness funds are not able to predict future health care expenditures of consumers more accurately by gathering more relevant information. This system should guarantee that they would receive more money for higher-risk patients and so would not discriminate them.

Therefore, the best possible solution is to design the premium distribution in a way that the fees for each patient are connected to his or her future health care expenditures or with retrospective compensation of expenses of insurers. This could be done either by allowing insurers to *risk rate the premiums* they get from consumers or by developing *risk equalization model* with more accurate and predictive risk adjusters. The former brings

unequal charging of high-risk and low-risk patients, which is in contradiction with solidarity. Third strategy is based on *risk sharing* between sickness fund and Central Fund (Van Kleef et al. 2013). However, this strategy should be done carefully to ensure that it would not lead to inefficiency, when there is a guarantee of costs compensation (van de Ven et al. 2004). In these days there exist models which combine prospective premium distribution with risk sharing in the form of retrospective compensation of some concrete extremely high insurers´ expenses.

The first risk adjusters are based on demographic factors, however nowadays can be already seen as too simple without too high cost predictive power. The main changing factor in the population in recent years is tendency of growing life expectancy accompanied by more and more people suffering from chronic diseases. Thus, patterned after countries, where this technique of risk adjustment was already implemented, Slovakia introduced *Pharmacy-based Cost Group (PCG) model* in 2012 and afterwards also Czech Republic in 2018. The PCG model is built on the information regarding previous drug consumption of the patients according to which are individuals then assigned to different kinds of chronic disease groups. This sort of information should increase the predictive accuracy compared to previously used sole demographic classifications.

Even though the motivation for this topic came from introduction of PCG model in the Czech Republic, empirical part of my work would be based on Slovak data. However, as the models are today similar, conclusions from my work can be easily applied on Czech Republic as well.

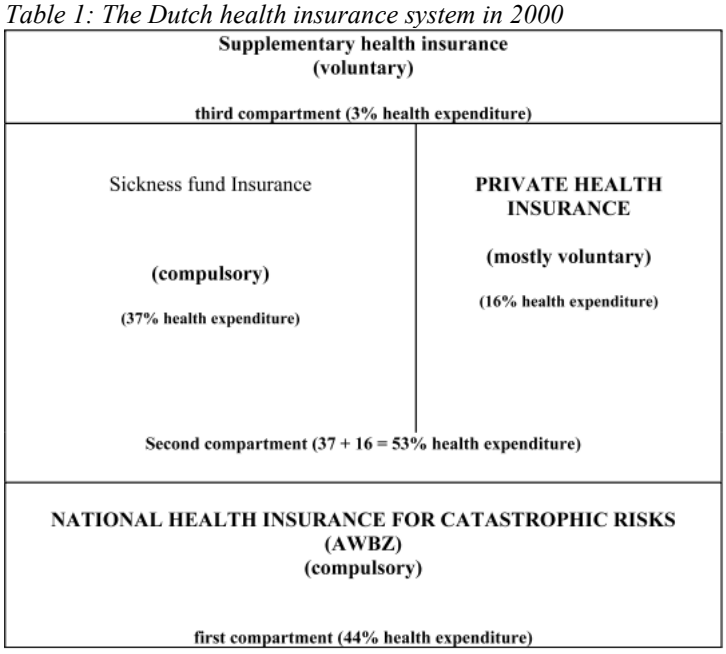
The first two parts of the thesis are mainly focused on the Netherlands and the reason is that it is the pattern for health care systems in Czech Republic as well as in Slovakia. So the formation of the mandatory health insurance and consequently also risk adjustment system in the Netherlands is very crucial for our region too. Afterwards the work focuses on development of the risk equalization model as it is known today, not only in The Czech Republic, but mainly in Slovakia as a crucial area for our oncoming analysis. The fourth part summarizes some considerable literature for the analytical part of the work. Then the methodology used for the research is described, followed by the results of the empirical part. Finally comes the discussion about findings and overall conclusion of the paper in the Chapter 9.

1 From solidarity to risk adjustment – the Netherlands

Before reform in 2006, the Dutch healthcare insurance system consisted out of three parts, depicted in *Table 1*. First part is a compulsory health insurance against too high expenses covering situations such as hospital care exceeding one year, long-term nursing home care or long-term institutional care for mentally and physically handicapped patients (Lamers et al. 2003). The second compartment is divided into two parts – first covers compulsory sickness fund insurance for people with income lower than by government set threshold, second voluntary private health insurance, mainly designed for short-term care. In the third voluntary compartment were included services beyond first and second one – mainly luxury hotel services when hospitalised, dental care for adults and prolonged physical therapy (Lamers et al. 2003).

This division is particularly important because several researches dealing with insurance sector in the Netherlands were written prior the 2006 reform and so focused just on the compulsory insurance part for people from the lowest income brackets, which covered around 62% of the population (Lamers et al. 2003). This is obviously for as much as the other parts of the Dutch insurance, meaning first and third containment and voluntary part of the second one, were not covered by risk adjustment system and its development.

Table 1: The Dutch health insurance system in 2000



Source: (Lamers et al. 2003)

Since January 1st 2006, the importance of adequate risk adjustment system even more considerably increased, as a result of the reform obliging the entire Dutch population to buy mandatory health insurance from one of the former sickness funds or some private insurer (Prinsze a van Vliet 2007). In other words, the risk adjustment system resulting in money distribution from the Central Fund to the insurers started to cover not just above-mentioned 62% of the lowest-income population, but the whole state. The other two compartments were not a part of the reform and so remained the same.

When it comes to the financing of the system, policymakers had to resolve the cherry-picking issue. Because the full cross-subsidization, meaning receiving equal payments for everyone which overcosts some patients and undercosts others which are then cross-subsidized by the overcosted ones, is unsustainable practise. In competitive market this would lead to lower and lower subsidy price and consequently coerce the sickness funds to either charge everyone with different premiums or select just low-risk individuals. To avoid these unintended actions which disrupt solidarity principle, but in the meantime to keep the market competitive, there was introduced a system, where premiums paid to insurers are distributed in two ways – there are *premium subsidies* received from the solidarity fund or Central Fund computed according to risk adjustment methods and

premium contributions (still in accordance with solidarity principle they are fixed nominal monthly payments) paid directly to the sickness funds as a difference between the whole premium and from Central Fund received premium subsidy. This kind of system, used in the Netherlands or Belgium, is called external subsidy system, as the subsidizing risk equalization is done outside of the funds. Then there is an alternative system, internal one, where the individual pays the whole contribution to the sickness fund and the fund consequently resolves the differences between premium subsidies and premium contributions with the solidarity fund on its own. This type of system is applied in Switzerland or Germany. The key is that the only difference between these two types of subsidy systems is in the way how the equalization is proceeded (de Ven et al. 2003).

Solidarity contributions to solidarity fund are mandatory and income-related, levied by the tax collector (Lamers et al. 2003). This ensures income solidarity as well as risk solidarity as the subsidies are risk-adjusted according to factors as sex, age or health status which would be used to define the amount of the premium in case the market would be unregulated (de Ven et al. 2003).

Still it is important to regulate not only risk-adjusted premium subsidies paid to the solidarity fund, but also premium contributions. Otherwise there is still a place for sickness funds to charge people unequally regarding their riskiness. Hence, there were taken restrictions towards these contribution payments and government insisted on equal premium contributions for all enrolees within the same insurance company. Premium contribution, however, vary across the sickness funds, what makes a tool for market competition among insurers. Together with an open enrolment period, during which all applicants have to be accepted by the funds, there is created appropriate surroundings for competitive market with solidarity features. However, the market seems to be still imperfect. The insurers are using less obvious methods of adverse selection. These involve practises like giving poor service to the chronically ill or not contracting with providers who are known to specialize in treatment of chronically ill patients. There are a few ways how to optimize the selection issue. One of them is effective *ex-post risk sharing* between insurers and Central Fund. In 2001 this accounted for 65% of the costs in the Netherlands. This high number may indicate poorly set risk sharing system with possible results of lowering efficiency and cost containment of sickness funds (Lamers a Van Vliet 2004). Though insurance companies are willing to bear more financial risk only in case that at the

same time the premium subsidy calculations would capture expected costs more precisely. The space for improvement of the health care insurance system is therefore in better design of *risk adjustment*. Its gradual improvement ensured also in the Dutch health care system that nowadays the whole financial risk bear the insurance companies (Wammes et al. 2014).

2 Development of risk adjustment

Countries like Slovakia and Czech Republic decided to rebuild the existing risk adjustment model according to a pattern seen in the regions, where the upcoming model already existed and worked well. The first of them, by many others viewed as an example in health care sector, more concretely risk adjustment improvements, is Netherlands. Reported better results in the field lead afterwards also Slovakia to follow the change to PCG model, which Czechs adopted recently too.

2.1 Muster in Netherlands

The adequate risk adjuster should meet certain criteria. It should lead to *appropriateness of incentives*, in other words to efficiency of insurance companies and better services provided for people pointing to increasing health conditions. Then it should establish *fairness*, meaning improve solidarity in availability of health care in society. And at last but not least, essential is a *feasibility* of data – the adjuster should be measurable and data should be accessible within reasonable costs (de Ven et al. 2003). Along with these criteria Lamers and Van Vliet (2004) propose another crucial characteristics – risk adjuster should be *invulnerable to manipulation* from insurer´s, provider´s or insuree´s side.

We can claim that the whole change towards risk adjustment began in 1992 when the policymakers decided to reshape the allocation of money to sickness funds (van de Ven et al. 2004). By then the system was set up retrospectively, meaning that the funds received full reimbursement for all the expenses on health care from Central Fund. The reform introduced prospective payments in a form of premium subsidy per head according to used risk adjustment method. The main reason was to shift a part of financial risk of potential losses but also gains to insurance companies. This should eliminate moral hazard connected with the certainty of reimbursement of costs. Besides that, the reform enabled

people to freely choose the sickness fund of their preference with guarantee that during an annual open enrolment period they cannot be refused by the insurer.

In upcoming sections I will take a closer look on the development of model according to risk adjusters added to the model and resultant improving costs predictive accuracy of the models. By researchers broadly used method for evaluating predictive power is taking into account subgroups of extremely high-risk or low-risk people for which the model usually does not perfectly compensate the expenses. Simply looking just at the R-squared does not have high informative value, as we do not know what the maximal R-squared for predictable variation in expenses is and so we are not able to perform any comparative analysis. Nevertheless, R-squared can be used as supportive indicator as well when comparing several different models.

2.1.1 Demographic adjusters

At the turn of the eighties and nineties, there were several studies conducted to find out what predictive factors should be included in the capitation formula. It resulted in initial usage of easily accessible adjusters which certainly show different health care needs. Consequently, first Dutch risk adjustment model was based just on gender and age groups. The model was introduced in 1992 and in this basic form was used during following two years. In 1995 were added clusters of region factors, in 1999 source of income interacted with age (Van Kleef et al. 2013). Initially there were 20 classes for men and 20 for women – 0, 1-4, 5-9 up to 89 and one group for people of 90 years old and older. Then they were completed with 10 clusters of regions and final demographic model included also 17 source-of-income-age classes. Income sources are divided into 4 subgroups – self-employed, disability benefits, social security benefits and other, which includes also employment. They are interacted with either 18-34, 34-44, 45-54 or 55-64 age classes. Those under or above this age categories are added into one separate group.

2.1.2 Pharmacy-based Cost Group (PCG) adjuster

Already from the beginning of the health care reform it was believed that using just demographic factors for the model construction is insufficient. What is needed for more accurate expenditure prediction is a data-reachable proxy for health status of the enrollees. Therefore in 2002 the Dutch government imposed the adjuster known as *pharmacy-based cost groups*.

This variable is based on the believe that past drug consumption of patients might serve as an indicator of chronic illnesses. An enrollee is classified into the PCG group according to his or her consumption of specific pharmaceutical during previous year. So that the user of the medication is not incidental, but really chronically ill, the consumption must exceed 180 defined daily doses (DDDs) and a person could not belong to more PCG groups at the same time – he or she is assigned with the costliest one. This was limited to prevent insurers from gaming possibilities, so that the ones who were already added to some PCG were not prescribed any additional drugs so to fall into another chronic-illness category. When the PCG model was launched, there were 13 groups. After few modifications, nowadays it increases to 26 PCGs with one group for those who based on the DDDs allocation do not enter into any of them, i.e. do not suffer from any chronic illnesses. What is more, the restriction for the number of allocated PCGs was eased and patients can be now allocated into more than just one group.

The whole idea began with the research of Lamers and Van Vliet (2004), who in their work validated the reasonability of PCGs introduced into the Dutch insurance sector. They were investigating the revised version of the chronic disease score (CDS) – measure of chronic disease status based on pharmacy data representing some chronic disease – constructed by Von Korff in the US. There were formed 28 different conditions with all the anatomical therapeutic chemical (ATC) codes – indicators of prescribed medication for the diseases grouped into one CDS. These CDS were revised to the Dutch environment, i.e. some of the CDS were omitted, because prescribed medication is in the Netherlands used also for acute care or some CDS were put together, as they are too closely related or because of other similar reasons. This process ended up in 22 CDS, whose reasonability for the Netherlands was confirmed. Out of these 22 CDS, 13 were consequently actually used

in the risk adjustment model as PCGs. Excluded were those which are covered by other two compartments in the Dutch system, or which were not prescribed in relevantly high amount, previously mentioned at least 180 DDD. Excluded were also chronic conditions whose costs were not underestimated significantly by using simple demographic model, so that the gaming possibilities are reduced as much as possible. The whole investigation resulted in 13 pharmacy-based cost groups applied in the Netherlands.

However, there are still left some gaming possibilities coming with PCGs. For instance, inefficient providers might be rewarded and there can be a pressure on providers to prescribe more drugs than necessary or selecting contracting with providers.

2.1.3 Diagnostic Cost Group (DCG) adjuster

As PCGs are outpatient health status proxy, so are DCGs inpatient health status proxy, what should make these two perfect complements (van de Ven et al. 2004). This adjuster was introduced in 2004 with 13 DCGs and one reference group – *no DCG*. The idea is to divide people according to their previous year hospital diagnosis into rather homogenous cost groups (Van Kleef et al. 2013). People can be added only into single DCG, again to the one with highest follow-up costs.

2.1.4 Other predictors added

In 2008 there was another reform concerning currently used risk adjustment model, which came with 12 *classes of socioeconomic status interacted with age*. Socioeconomic status is a mixture of income and number of people in one household – each person´s income is a proportion of total household income and number of household members. Then there are 4 socioeconomic classes – those in the bottom 30% of income distribution, 30%-70% and above 70% and separate category for those living in the family with more than 15 people.

So far as the last adjuster the Netherlands set *high costs in multiple prior years*. There are totally six groups based on the previous healthcare costs during *t-3*, *t-2* and *t-1* years plus one group for those who do not belong to any of these. This classification relies on assumption that those enrollees whose costs were too high within several prior years may suffer from some chronic disease (Van Kleef et al. 2013).

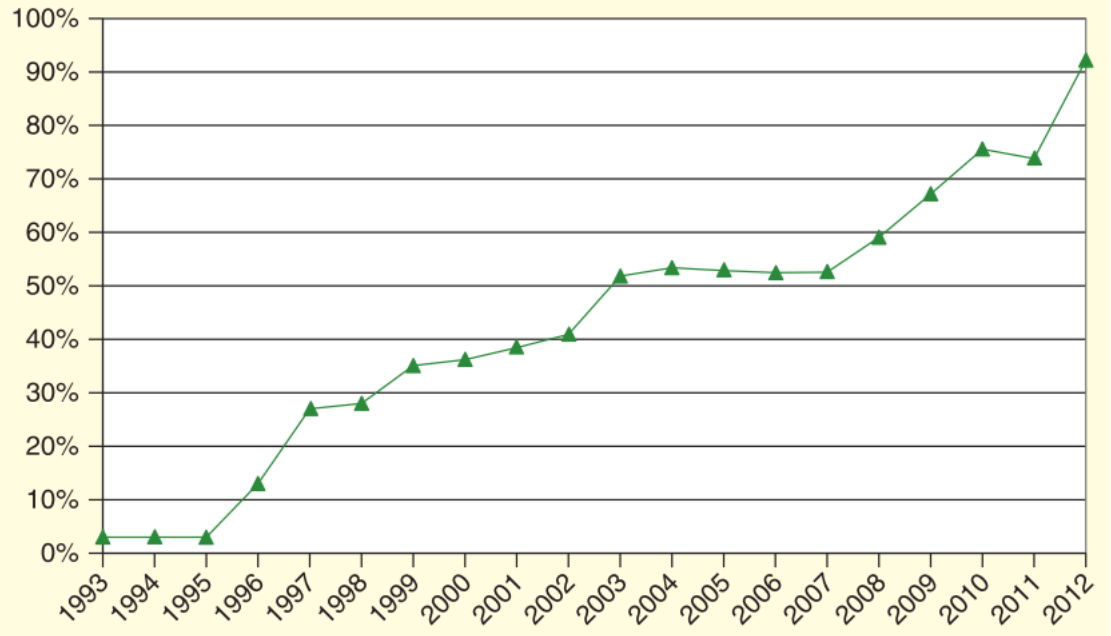
2.1.5 Risk sharing

The Dutch risk adjustment model is already from the beginning supported by *risk sharing* between the equalization fund and sickness funds. As was already mentioned before, crucial thing is to set it in a way that incentives for efficiency and cost containment would not be disturbed. On the other hand, the lower the risk sharing, the higher are the incentives for risk selection. Therefore, it is important to make changes in financial risk responsibilities together with increasing accuracy of risk adjustment model. The Dutch government conducted several measures to change the initial setting of risk sharing, which provided insurance companies with certainty that their extreme costs would be covered by the state.

With introduction of risk adjustment system, the initial financial risk borne by the sickness funds accounted for only 3%. Remaining 97% of potential loss or gain was shared with the Central Fund. From that time, the responsibility of insurers enhanced visibly – the changes are captured in

Figure 1. According to latter figures, the ex post compensations were cancelled and insurers bear already the full risk (Wammes et al. 2014).

Figure 1: Development of average financial risk for sickness funds



Source: Van Kleef et al. 2013

Notes: Financial risk for medical costs covered by the basic benefit package excluding the costs for curative mental health care.

2.1.6 Changes in predictive accuracy

When looking purely at R-squared, van Kleef et al. (2013) found out that the most important factors in these risk adjustment models are age and sex, PCGs, DCGs and multiple-year high costs. They moreover constructed seven models based on the risk adjusters described in previous sections and actually used in practise in the Netherlands, applied them on their data and reported estimated R-squared, see *Table 2*. The model 7, which is actually applied in practice today, reported almost 30% R-squared compared with nearly 6% in the first demographic model. Consequently, we can conclude that the predictive power of the risk adjustment models undoubtedly increased within years, although we cannot express how sufficiently it forecasts the whole predictable variation in costs.

Table 2: Health care expenditures regression models based on 2009 data

Model	Description	R-squared × 100%
0	Constant (no risk adjusters)	0.00%
1	Model 0 + 40 classes for age/gender	5.97%
2	Model 1 + 10 clusters for region	6.01%
3	Model 2 + 17 classes for source of income	6.83%
4	Model 3 + 26 PCGs	15.92%
5	Model 4 + 14 DCGs	24.99%
6	Model 5 + 12 classes for SES	25.04%
7	Model 6 + 7 classes for MHC	29.61%

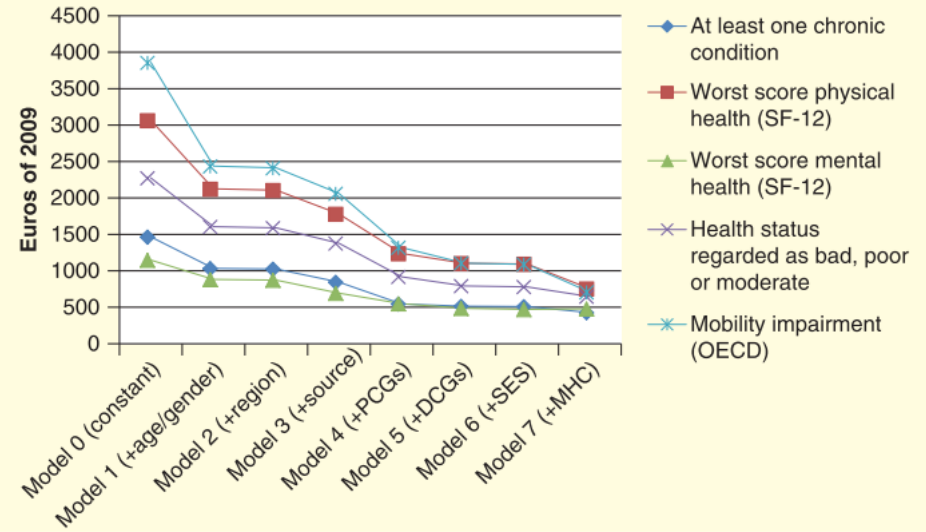
DCGs: Diagnoses-based cost groups; MHC: Multiple-year high cost; PCGs: Pharmacy-based cost groups; SES: Socioeconomic status.

Source: Van Kleef et al. 2013

As was already mentioned, method of R-squared evaluation has less to say than investigation of for example expenses of individuals in poor health. Van Kleef et al. (2013) provided also this kind of analysis. By performing a survey, they defined several categories of people in poor health and evaluate under- or overcompensation per model per subgroup. The findings showed that with more and more relevant risk adjusters added into the risk equalization model, the undercompensation of the costs decreases significantly. Results for five specific subgroups included in survey for poor health conditions are displayed in *Figure 2*.

Authors pointed out that the overall undercompensation for all of the 18 poor-health subgroups decreased with model 7 – which is actual model used in the Netherlands now – compared to initial model 0 – without any adjusters, so subsidies are based just on average population costs – by 47% for headache problems to even 90% for people who suffer from obesity. Still it has to be concluded that even the so far final model undercompensates all of the subgroups.

Figure 2: Undercompensation in year 2010 for 5 specific poor-health subgroups (based on 2008 survey)



Source: Van Kleef et al. 2013

In terms of R-squared are reported also results of paper by Prinsze and van Vliet (2007), depicted in *Table 3*. The paper relies on administrative data for years 2000 and 2001 for 24 sickness funds in the Netherlands. As the authors incentive was to study predictive power of PCG and subsequently PCG+DCG model. They suggest, the R-squared after inclusion of PCG predictors to demographic model enlarged from 6,5% to 11,8%. What is more, the PCG+DCG model increased not only overall expenses R-squared, but also predictability for both outpatient as well as inpatient expenses.

As other determinant for improved predictability authors computed *predictive ratio* – proportion of expected costs over actual costs, see *Table 4*. Basically, the closer to one the ratio is, the higher predictive accuracy model has. Even the sole PCG model shows quite close-to-one predictive ratio, inclusion of DCG caused ratio to be almost equal to one for all examined subgroups – 0,99 for no PCG, DCG subgroup means the model slightly undervaluates real costs and on the other hand 1,01 for PCG, DCG group indicates just small overvaluation.

Table 3: Predictive accuracy of 4 models in terms of R-squared (%)

Model	Outpatient expenses (%)	Inpatient expenses (excluding fixed hospital costs) (%)	Total expenses (excluding fixed hospital costs) (%)
Demographic	7.8	3.3	6.5
PCG (old)	19.7	4.9	11.8
PCG (revised)	23.7	4.3	11.5
PCG+DCG	27.1	15.6	22.8

Source: Prinsze a van Vliet 2007

Table 4: Predictive ratio (expected costs/actual costs)

Subgroups		PCG model	PCG+DCG model
No PCG	No DCG	1.02	1.00
PCG	No DCG	1.04	1.00
No PCG	DCG	.77	.99
PCG	DCG	.89	1.01

Source: Prinsze a van Vliet 2007

Van de Ven et al. (2004) simulated five risk adjustment models gradually applied in the health care system in the Netherlands on enrollees data from five sickness funds. In the paper are reported results of predictive accuracy in year *t* for 10% of people with highest expenses in year *t-1* together with R-squared of these regressions, as depicted in *Table 5*. We can see the growing tendency of R-squared as the amount of risk adjusters added increases. Apart from that, results show exactly what can be predicted from theory – R-squared jumped markedly after introduction of PCGs into the model. The difference was

not so significant after inclusion of DCGs, i.e. PCG+DCG model, but what was proven is more suitable predictive power for inpatient expenses.

More relevant conclusions can be based on reported average predicted losses, which is a difference between average predicted expenses and average actual expenses in year *t*. We can sum the findings in pretty similar way as in case of R-squared. The percentage of average losses from total average expenses decreased from 75% for the first demographic model with too crude adjusters, through 43% with PCGs to "only" 30% for the most sophisticated model from the reported ones – PCG+DCG, meaning that 45% of expenses were successfully predicted in advance thanks to inclusion of more and more risk adjusters.

Table 5: Predictive accuracy of 5 simulated risk adjustment models

	Model					
	No risk adjusters	**Demographic I**	**Demographic II**	**PCG**	**DCG**	**PCG + DCG**
R2 x 100% for each model (percent explained variance)						
Outpatient expenses	0.0%	6.9%	7.8%	19.7%	11.3%	21.8%
Inpatient expenses[a]	0.0	2.2	3.3	4.9	8.6	9.5
Total expenses[a]	0.0	5.5	6.5	11.8	12.6	16.6
Predicted losses in year *t* of 10 percent of people with highest expenses in year *t*−1						
Average predicted expenses (Euro)	875	1,350	1,443	1,967	2,046	2,418
Average predicted losses (Euro)	2,558	2,083	1,990	1,466	1,387	1,015
Average predicted losses as percent of average actual expenses	75%	61%	58%	43%	40%	30%

Source: van de Ven et al. 2004

Notes: Average expenses in year t are 3 433 EUR. The five risk-adjustment models are as follows. Demographic I: Age and sex (used in 1992–1994). Demographic II: Age, sex, urbanization, and eligibility status (for example, employed or not employed, disabled) and age x eligibility status (used in 1999–2001). PCG: Demographic II plus Pharmacy-based Cost Groups (PCGs) (used in 2002–2003. DCG: Demographic II plus Diagnostic Cost Groups (DCGs). PCG + DCG: Demographic II plus PCGs and DCGs.

[a] *Excludes fixed hospital costs.*

3 Health Care System in Czech Republic and Slovakia

3.1 Czech Republic

As it is in Netherlands, also Czech Republic applies mandatory health insurance for everyone who is employed in the Czech Republic or have residence there. On the other hand, according to solidarity principle health care is provided to everyone, also for people who do not contribute to the system. The contributions, which are paid directly to the insurance companies, are made by 4,5% share of taxable income from employees´ side and 9% from employers´, forming together 13,5%. The same proportion are obliged to pay also self-employed from 50% of their profit, with a certain minimum contribution per month, which changes slightly each year (2 024 CZK in 2018). People without taxable income pay their part on their own with minimal per month contribution of 1 647 CZK in 2018 (VZP 2017). Exceptions from compulsory payment are for unemployed, pensioners, students, women on maternity leave, prisoners, soldiers and people receiving social security benefits. These contributions are made by the government itself with 787 CZK per month for each enrollee. They are collected in the Redistribution Fund and accounts for up to 58% of overall contributions to the insurers (Kancelář zdravotního pojištění 2016).

There are 7 non-for-profit insurance companies operating in the country today, see *Table 6*. Similar to the Dutch pattern, there is an open enrolment period each year, within which people can freely change the insurer.

Table 6: Insurance companies in Czech Republic as of 31.12.2016

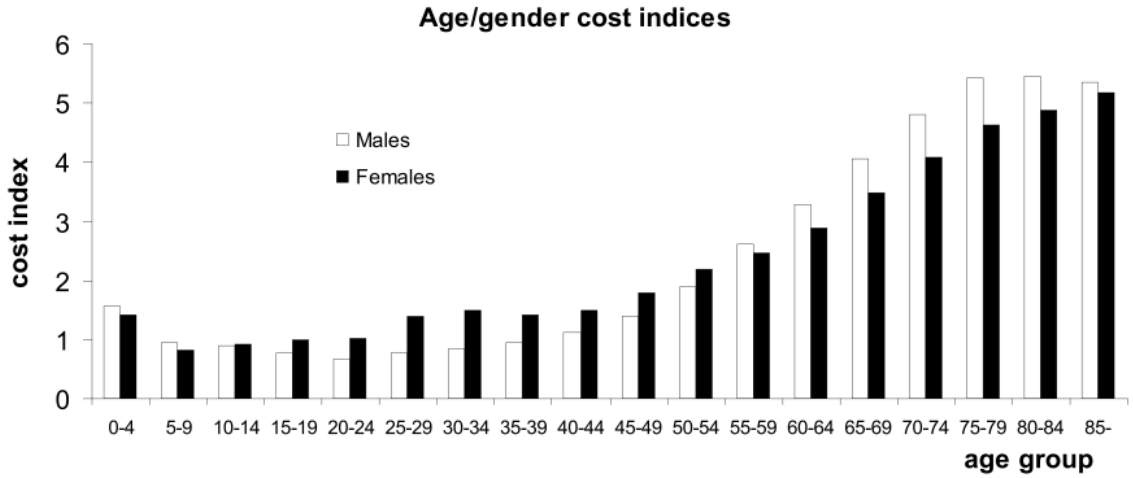
INSURANCE COMPANY	NUMBER OF ENROLLEES
VŠEOBECNÁ ZDRAVOTNÍ POJIŠŤOVNA ČR	5 909 000
VOJENSKÁ ZDRAVOTNÍ POJIŠŤOVNA ČR	700 500
ČESKÁ PRŮMYSLOVÁ ZDRAVOTNÍ POJIŠŤOVNA	1 242 000
OBOROVÁ ZDRAVOTNÍ POJ. ZAM. BANK, POJ. A STAV.	728 900
ZAMĚSTNANECKÁ POJIŠŤOVNA ŠKODA	142 700
ZDRAVOTNÍ POJIŠŤOVNA MINISTERSTVA VNITRA ČR	1 299 600
REVÍRNÍ BRATRSKÁ POKLADNA, ZDRAV. POJIŠŤOVNA	431 000

Source: Křeček 2017

3.1.1 Risk Adjustment in Czech Republic

First risk adjustment model based on relevant risk adjusters was launched in 2005. The predictors used were the most basic ones – gender and age. There were all together 36 group interactions of age and sex as depicted in *Figure 3*.

Figure 3: Cost indices for age-gender groups in Czech Republic, 2010



Source: Chalupka 2010

This old, and as already previously described too crude and not precise model will be finally revised also in Czech Republic. Already from this year (2018) the risk adjustment should be supplemented by pharmacy-based cost groups. As a pattern the reform used PCGs in the Netherlands with implemented minor changes. How exactly the new PCG model looks like is described in next section.

3.1.2 New PCG Model in Czech Republic

When talking about age-gender cost groups there is a slight change compared to model used so far – initial 36 groups were extended by one more group for each gender. The reason is that health status of newborns is considered to be riskier than that of children between 1 and 4 years old. These were previously joined into one group. Apart from this there are newly introduced 25 PCGs as shown in *Table 7*.

Table 7: PCGs used in new Czech risk adjustment model

NUMBER	CODE	NAME
1	GLA	Glaucoma
2	THY	Thyroid disorders
3	PSY	Antipsychotics, Alzheimer's disease, addiction treatment
4	DEP	Treatment with antidepressants
5	CHO	Hypercholesterolemia
6	DMH	Diabetes with hypertension
7	COP	Chronic obstructive pulmonary disease and severe asthma
8	AST	Asthma
9	DM2	Type II diabetes
10	EPI	Epilepsy
11	CRO	Crohn's disease, ulcerative colitis
12	KVS	Heart disease
13	TNF	Rheumatic diseases treated with TNF inhibitors
14	REU	Rheumatic diseases treated differently as with TNF inhibitors
15	PAR	Parkinson's disease
16	DM1	Type I diabetes
17	TRA	Transplants
18	CFP	Cystic fibrosis or pancreatic exocrine disease
19	CNS	Brain and spine disorders
20	ONK	Malignancy
21	HIV	HIV/AIDS
22	REN	Renal failure
23	RAS	Growth hormone therapy
24	HOR	Hormonal oncology
25	NPP	Neuropathic pain

Source: Zákon České národní rady o pojistném na všeobecné zdravotní pojištění 2018

Each insuree is assigned to all PCGs according to his/her drug consumption with corrections for PCG concurrence. *Risk index* of an enrollee is than computed as a sum of 1, cost index of age-gender group, cost indices of his/her PCGs and corrective cost indices.

Although the motivation to choose this topic for my paper was thanks to the changed legislation and consequently introduction of PCG RE model in Czech Republic, from now on the work would be focused primarily on Slovakia, mainly empirical part. Still, as the systems and risk adjustment models are nowadays almost identical, outcomes from my thesis can be widely applied to the Czech Republic as well.

3.2 Slovakia

There are many similarities between health care system in Czech Republic and Slovakia. First of them is that also Slovakia applies compulsory health care insurance on the whole population. Premiums are collected from employees, employers, self-employed, dividend payers, voluntarily unemployed and the state. Generally, employee contributes with 4% from his/her annual income, employer with 10% from employee´s annual income, self-employed with 14% as well as dividend payer and voluntarily unemployed. State contributions are made for retired persons, students, people on parental leaves, unemployed etc. Also in Slovakia there are set minimum contributions for self-employed and voluntarily unemployed – this amount should form at least 50% from average wage of employee in Slovak economy within year two years preceding the decisive year. State allocates part of the state budget for insurance of those who do not contribute themselves, which was set to be used for this purpose according to law. This part is divided among insurers based on by each sickness fund announced number of people who are entitled to state support (Zákon Národnej rady Slovenskej republiky 2004).

Nowadays there are three insurance companies in Slovakia, together with number of their enrollees listed in *Table 8*. Also Slovakia offers once a year costless option to change the insurer.

Table 8: Insurance companies in Slovakia as of 1.1.2018

INSURANCE COMPANY	NUMBER OF ENROLLEES
VŠEOBECNÁ ZDRAVOTNÁ POISŤOVŇA	3 192 861
ZDRAVOTNÁ POISŤOVŇA DÔVERA	1 478 854
ZDRAVOTNÁ POISŤOVŇA UNION	477 617

Source: Úrad pre dohľad nad zdravotnou starostlivosťou 2017

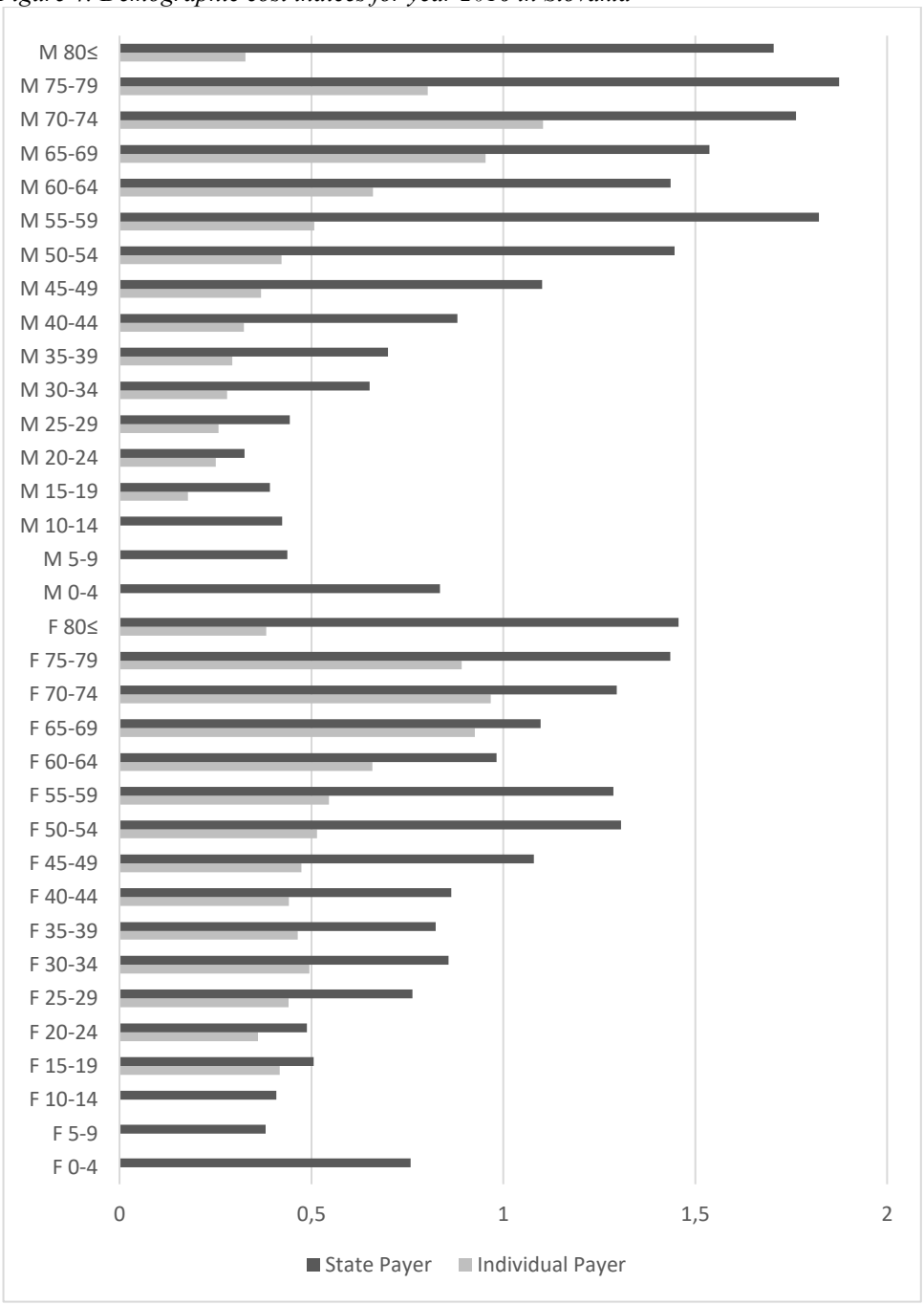
3.2.1 Risk Adjustment in Slovakia

Since 1993 when the history of segregated republic began the system of premium redistribution evolved a lot. Till 1995 there was only one national sickness fund and hence no premium allocation was needed. After the adoption of the new law establishment of more insurance companies was allowed. They were obliged to forward 60% of collected premiums to redistribution fund. This number increased during years up to currently set 95%. Allocation of resources was based just on number of enrollees with higher weights on economically inactive people, which were considered to be people above the age of 60. From 1999 the coefficient for people older than 60 was replaced with sex-age groups gathering always five years into one group with computation of risk indices. In 2005 the resolution fund is being liquidated. Thenceforth *Úrad pre dohľad nad zdravotnou starostlivosťou* monitors receivables and payables among insurers. Demographic factors were from 2010 supplemented by economic activity/inactivity of insurees (Glova a Gavurová 2013).

PCGs as predictors were introduced in Slovakia already in 2012. We can see that unlike in Czech Republic, Slovakia has not used separate age group for newborns yet. In addiction the highest age group is for 80 and more years (not 85 and more), so there are only 17 age categories for each gender. Besides that, in Slovakia the age-gender demographic factors are supplemented by binomial variable distinguishing whether the enrollee pays the premium himself/herself and so is economically active or it is paid for by the state, let´s refer to this as *payer status*. Demographic cost indices computed for year 2016 are shown in

*Figure **4***.

Figure 4: Demographic cost indices for year 2016 in Slovakia

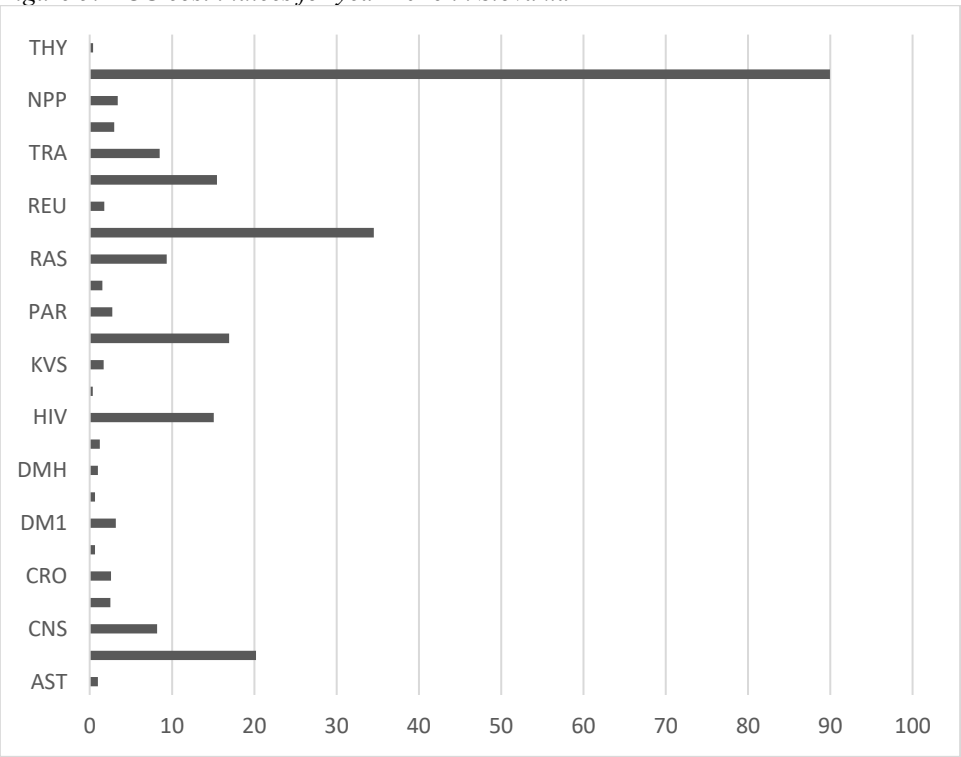


Source: Vyhláška Ministerstva zdravotníctva SR 2015

PCG groups used in Slovakia are almost identical with Czech legislation, apart from *Glaucoma,* which is currently removed from PCG list and Hemophilia, which is on

the other hand classified as PCG in Slovakia. One quite substantially different characteristics of Slovak RE model compared to Czech Republic or even currently used model in the Netherlands is that in Slovakia each person can be classified to *no more than one* PCG (the costliest one). Again, cost indices for year 2016 are displayed in *Figure 5*.

Figure 5: PCG cost indices for year 2016 in Slovakia



Source: Vyhláška Ministerstva zdravotníctva SR 2015

Apart from payments which insurance companies receive each month in advance, the Slovak law allows also ex-post compensation of extremely expensive patients. This support is set so that above certain threshold state covers 80% of costs while the rest still pays the insurance company. This is covered in more detail in *Methodology*.

4 Literature Review

One of the main aims of improving models for resource redistribution among insurance companies is fair allocation of resources. In other words, it is important to achieve positive or at least zero profit of each PCG for all effectively operating insurers. Only in that case insurers would be motivated to compete and improve the care for everyone, including chronically ill patients. Profit or loss of PCG is basically difference between how much company receives for a patient from redistribution fund and how much it actually spends on him within some certain period of time. There is a strong believe that in majority of cases the results are negative for companies, what unfortunately supports perverse incentives of adverse selection. The goal of my research should be to confirm or refute this assumption. Next, I would like to propose what can be potentially done to improve the compensation of health care costs.

We suppose there may be two potential reasons for loss over PCGs. Either the issue lays in time delay of the data used for computation of risk indices and/or there is a problem with the difference in frequency of resources allocation between the Netherlands where the model was developed and Slovakia or Czech Republic, which uses it as a pattern. The former is connected to the fact that for computation of risk indices for redistribution in year *t*, there are used data about insurees drug consumption and their belongings to the cost groups from year *t-3*. Three years is pretty long period within which lot of might change – from pharmaceuticals and methods used for cure to costs of care. The latter supposes that model could work better in the Netherlands, because they allocate money once a year, while in Slovakia as well as the Czech Republic this process repeats monthly. These are however hypotheses that I am not about to focus on in my work.

Moreover, the problem with profit or loss over PCGs can also appear when the PCG does not cover all the people who really suffer from the disease. There is threshold of 181 DDDs set by law to be added to certain PCG. As was already mentioned, this should prevent from accidental assignment of a person into the PCG or perverse incentive of insurer to artificially increase the amount of prescribed drugs to obtain more resources for

someone who actually is not chronical patient. However, it is argued that 181 DDDs are too many to catch everyone with certain illness. We should not believe that a person who was prescribed for instance 150 DDDs is not real chronical patient. Obviously, also this proportion of drugs can be viewed as too high for acute care or attempt for perverse incentive by insurer. Therefore, it might be reasonable to check whether the threshold should not be lowered or there should be added another group for some chronic illnesses indicating lower but still relevant usage of medication.

According to van Kleef, van Vliet, van de Ven (2016) one possible solution for insurers´ loss over PCGs is overpaying these adjusters. They are concerned about the abovementioned problem with DDDs threshold. Regarding their suggestion, money intakes that insurers receive for each PCG can be increased on top of the average expenses of that PCG by certain amount. This amount should ensure that the whole group of people who used the relevant drugs for the PCG during examined year (those with at least 1 DDD) are sufficiently compensated, i.e. their undercompensation is equal to 0. The rationale behind this is that when the whole group of people who consumed relevant drugs is undercompensated, the complementary group of people with 0 DDD is overcompensated and so creates a space for adverse selection. Still there are three preconditions needed to be fulfilled to be able to apply this strategy. First of all, one has to possess information about population frequency, average expenses and predicted expenses for people assigned to the PCG (marked in the paper as group X), for the ones with at least 1 DDD of relevant drugs (group XY) as well as for those with 0 DDD (group Z). Secondly, when the group X is overpaid, not only payments for group Z would decrease (actually, overcompensation would be equal to 0), but also undercompensation of people between 1-180 DDD (group Y) would deepen. Therefore, one should be sure that risk selection against whole XY and in favour of Z should be bigger issue than risk selection against Y and in favour of X. And eventually, according to authors group X itself should sufficiently fulfill criteria of risk adjuster as were already described before. Even if the adjuster was initially approved by the law, using overpayment method may change appropriateness of the adjuster and so should be checked again.

Similar issue was examined by Lamers and Vliet (2003), when they compared different levels of PDDs[1] for assignment of a person into the PCG and their effect on R-squared of the estimated models. In their study there is no possibility for a patient to be added to more than just one – the most expensive one – PCG. Tested thresholds were more than 4 PDDs, more than 91 PDDs and more than 181 PDDs. Results showed that the model with the highest R-squared is the one using 91 PDDs threshold (9.79%), while the lowest R-squared has 181 PDDs model (9.15%). However, it is crucial to add that these differences are negligible in terms of interpretation which model is the best-fitting one. Therefore, authors conclude that the model with at least 181 PDDs is preferred one. Their justification is supported by the assumption that the highest possible threshold reduces the gaming possibilities in the best possible way.

On the other hand, it might be reasonable to evaluate model using threshold of 121 DDDs, as done by Hajíčková (2015) in her master thesis. Her goal was to increase predictive accuracy of demographic model used in that time in Czech Republic by adding PCGs as predictors. Risk equalization models allowing for more than just one PCG, but without any correction for multiple assignments, are used. According to her results, PCGs bring considerable contribution to accuracy of costs prediction. What is more, she finds out that 121 DDDs yielded higher value of R-squared (19.47%) than 181 DDDs (18.51%). Apart from R-squared, also *Mean Absolute Prediction Error*[2] (MAPE) and *Mean Absolute Relative Error*[3] (MARE) were evaluated as indicators of accuracy, both resulting in better performance of 121 DDDs model, see *Table 9*.

[1] Prescribed daily doses – compared to defined daily doses (DDDs) which are adjusted daily doses to capture average daily dose for a drug used for its main indication in adults, PDDs are actual prescribed amounts of drugs per day.

[2] MAPE is calculated as the average of the absolute differences between predicted and actual health care costs, indicating the lower the MAPE the more accurate the model is in costs prediction.

[3] MARE is defined as the average of absolute differences between predicted and actual costs divided by actual health care costs. Same as for MAPE, the lower values of MARE the better prediction performance of the model.

Table 9: Predictive accuracy of evaluated models

	R^2	MAPE	(SD)	MARE	(SD)
Model 1	0.0203	22 709	(118 704)	178.88	(1 929)
Model 2	0.0206	23 227	(118 933)	176.65	(2 004)
Model 3	0.1295	19 856	(115 934)	117.48	(1 295)
Model 4	0.1297	19 853	(115 929)	122.78	(1 347)
Model 5	0.1387	19 775	(115 685)	111.61	(1 229)
Model 6	0.1389	19 770	(115 680)	116.94	(1 280)

Source: Hajíčková 2015
Notes: Model 3 stands for PCG model using 181 DDDs, Model 5 for PCG using 121 DDDs.

Last but not least, models differ also in how they deal with outliers, which may skew the costs of overall group. This happens mainly in groups with lower number of patients, where already a few can misinterpret actual costs of the PCG. Anyway, the distribution of healthcare costs is usually right skewed with heavy tail and so the outliers are problem also for large-enough datasets. Most of the models use method of cutting off extremely high costs. A matter of discussion is where to set the line above which the costs are compensated at least partly *ex post*[4].

Problem with outliers can be also solved by using *multiple-year high cost* as a health indicator. As van Kleef and van Vliet (2012) showed in their paper, applying this method may sufficiently improve predictive ratio of risk equalization model. The strategy is so that enrollees whose costs are in top 15% during 3 following years preceding the year for which risk adjusters are computed are about to obtain additional compensation. This paper compare compensation applied retrospectively as mentioned already above with the prospective approach designed as multiple-year high cost adjuster. Retrospective payment should be a percentage of actual costs of the year. Prospective payment requires adding additional adjuster into the risk adjustment model. This can be done either as fixed adjuster or as continuous variable for average costs in those three years (van Kleef a van Vliet 2012). There are studied different subgroups of people who were undercompensated in at least one of those three years. Results indicate that retrospective as well as prospective cost payment upgrades the predictive ratio of the model with prospective continuous approach bringing the highest improvement, i.e. for the subgroup with highest undercompensation

[4] In reality the Czech law as well as Slovak are written so that insurers allocate each month ex ante by the law stated part of received premiums to cover extreme costs. At the end of the year there is conducted settlement between how much the companies actually spent for extreme payments and how much resources they had allocated for that. Consequently, settlements among insurers are conducted so that each insurer has the same share of extreme costs covered.

by initial RE model – those who were undercompensated in each of the three preceding years – the predictive ratio increased from 0.52 to 0.83.

5 Methodology

5.1 Estimation process

My first aim would be to determine whether the risk indices computed via currently used model lead to loss or not. If so, my analysis should modify their computation over a specific subgroup of enrollees and try to improve the results.

The most straightforward way would be to compare nationwide risk indices, which were officially used for the desired year with the ones I would come up with in my varied model. However, as long as I know, the portfolio of insurees of just one specific insurance company does not have to possess same characteristics as the whole population does. As a consequence, this comparison might end up with misleading results. Therefore, first of all I have to set currently used model on the whole tribe of enrollees of the insurer and use these risk indices for comparison as if they are nationwide ones. Then just modify this official model according to my assumptions which may improve it and compute varied risk indices.

The computation of the cost indices would be done according to the prediction model currently used in Slovakia. Although we are dealing with time series dataset, the best feasible regression analysis is still considered to be ordinary least squares. The opponents argue that the distribution of health care costs cannot be estimated well by OLS (van Veen et al. 2015). However, the defenders believe that firstly it is crucial for policy makers to have model which would be easy to interpret and so not only that more complicated models are therefore inappropriate but nor transformations of variables are desirable. Consequently, simple levels of variables are preferred over logarithms or squared variables. Secondly, it is believed that for so large samples as are used in RE models, estimations by OLS are comparable with other more sophisticated models. And thirdly, for purpose of my analysis, I need to work with models having same properties as has the officially used one not to come up with differences due to distinct models used.

The whole process begins with fitting the model to data two years preceding the year for which we want to predict the costs (*t-2*) in case of demographic variables (age, gender and payer status) and health care costs and three years for drug consumption which determines PCG variables (*t-3*) (Zákon Národnej rady Slovenskej republiky 2004). Computed cost indices are afterwards used to predict health care costs in year *t* (in our case for year 2016) and compared with real costs of 2016 using two methods already described before.

5.1.1 Default Model Determination

As was already mentioned before, my default model would be based on actual risk adjustment model applied in Slovakia. The dependent variable y_i^* is difference between average monthly costs of each enrollee and overall average monthly costs, mathematically written as:

$y_i^* = y_i - \overline{y}$, where:

$y_i = \frac{c_i}{w_i}$, where c_i stands for annual health care costs of i[th] person and w_i is number of months when the person was insured and

$\overline{y} = \frac{\sum_{i=1}^{n} y_i}{n}$, where n represents number of all enrollees (Zákon Národnej rady Slovenskej republiky 2004).

Risk equalization model is then defined as:

$y_i^* = \alpha + \sum_{k=1}^{61} \beta_k x_{i,k} + \sum_{j=1}^{25} \gamma_j z_{i,j}$, where

parameters α, β_1,..., β_{61} and γ_1,..., γ_{25} are about to be estimated. It is essential to keep in mind why the model contains 61 dummies for demographic variables. There are all together 68 interacted classes for sex, age and payer status, however one class needs to be removed to avoid multicollinearity problem in the estimation process – this group is usually called reference group. The remaining six omitted classes are for children up to the age of 15, for which the payer of premium is always the state and so their parameters are automatically equal to 0. This is not the case for PCG groups, as there the reference group is *no PCG* and so we do not have to skip any of them.

$x_{i,k}$ represents dummy variables for interaction of demographic factors – sex, age and payer status (either the payer of premium is the state or the individual himself/herself),
$z_{i,j}$ then stands for dummies for each PCG group[5]. In our case, in year 2016 there were 25 PCG groups defined by the law.
α would be the intercept of the model and it would define the already mentioned reference groups of the model, e.g. when we omit dummy for men in the age between 0 and 4 years in the model, for which the payer is state, then the intercept α would be the parameter for these men who are not assigned to any PCG.

The predicted monthly costs of i[th] insuree that would be needed for MAPE and MARE evaluation would then look like:
$\hat{y}_i = \bar{y} + \widehat{\beta_{x_i}} + \sum_{j=1}^{J_{PCG}} \hat{\gamma}_j z_{i,j}$, where
x_i represents belonging of i[th] enrollee to one of 68 interacted groups of gender, age and payer status, but not within the estimated year *t-2*, yet in year *t* and so $\widehat{\beta_1}$,..., $\widehat{\beta_{68}}$ would be estimated parameters for demographic factors,
dummies $z_{i,j} = 1$ in case the i[th] enrollee belongs to the j[th] PCG group in year *t* and equals 0 otherwise and
$\hat{\gamma}_j$ is regression coefficient for j[th] PCG group (Vyhláška Ministerstva zdravotníctva SR 2012).

The fitted model can be rewritten as:

$$\hat{y}_i = \bar{y}(1 + \frac{\widehat{\beta_{x_i}}}{\bar{y}} + \sum_{j=1}^{J_{PCG}} \frac{\hat{\gamma}_j}{\bar{y}} z_{i,j})$$

By the model computed parameters would be then used to determine risk indices to model income of the insurer in the desired year *t*. *Risk indices* are computed as follows (Vyhláška Ministerstva zdravotníctva SR 2012):

$B_i = \frac{\widehat{\beta_i}}{\bar{y}}$, where B_i is known as demographic cost index

$C_i = \frac{\hat{\gamma}_i}{\bar{y}}$, where C_i is PCG cost index

[5] It is substantial to be aware of the fact that according to Slovak law, each person can be assigned to no more than one PCG group – the costliest one.

$1 + B_i$ is demographic risk index, in other words average risk index represented by unified 1 + deviation from average risk index.
C_i is PCG risk index, as additional index to demographic index.
Overall risk index of i[th] enrollee is then defined as $RI_i = 1 + B_i + C_i$.

5.1.2 Modified Model Determination

There are two hypotheses how the currently used RE model might be qualitatively improved when it comes to the PCG groups, what would be my point of interest:

i. Keep just one PCG group for each chronic disease, but lower the threshold of DDD of drug consumption for an enrollee to be assigned to the PCG group. As a proper threshold there is suggested to use 121 DDD. It is so because in one prescription there is usually three-month dosage, i.e. 90 DDD, what might be prescribed once on trial and so does not have to necessary mean the person is chronic patient. On the other hand, currently used 181 DDD stands for already more than 6 months of drug consumption and as was already written, this can skip some patients with lower consumption, but still ill. As a compromise one can suggest 121 DDD to be somewhere in the middle and so to include everyone who fit and still keep the threshold high enough to avoid random assignment as well as perverse incentives.

ii. Create ranges for each disease according to number of DDD, e.g. consumption of 91-120 DDD, 121-180 DDD, 181 DDD ≤. This would end up with several PCG subgroups for each illness.

5.2 Models comparison

Risk indices would not be compared just one to another, as it does not have much to say to us. I would use three methods for evaluation of the models´ performance. First of them computes *profit/loss* of the sickness fund by simply subtracting costs from calculated income. I would not take into account each component of costs of the insurer neither its intake, just parts which are relevant for my study, i.e. those that can be affected by changes in risk equalization model. So, my modelled profit/loss of company would consist of income after redistribution lowered by overall costs, where the overall costs would be real costs for each enrollee in year *t*. The income for one insuree is according to Slovak law as (Zákon Národnej rady Slovenskej republiky 2004):

$Income_i = standardized\ amount\ for\ 1\ recalculated\ insuree\ x\ risk\ index_i$, where

$standardized\ amount\ for\ 1\ recalculated\ insuree = \frac{overall\ redistribution\ basis}{number\ of\ recalculated\ insurees}$,

where

$number\ of\ recalculated\ insurees = \sum n_i\ x\ risk\ index_i$, where n_i is number of insurees in one of subgroups in year *t* – insurees according to gender and age where the premium payer is state, where it is not the state and number of insurees in each PCG group. However, we were not provided with information about overall redistribution basis, so we make a shortcut where we use instead sum of overall costs in year *t*. Then our standardized amount for one enrollee would be equal to:

$$standardized\ amount\ for\ 1\ recalculated\ insuree = \frac{overall\ costs\ in\ year\ t}{number\ of\ recalculated\ insurees\ in\ year\ t}.$$

The second method for evaluation of models would be *mean prediction error*. There can be either *MAPE* or *MARE*, computed as follows:

$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|C_i - \widehat{C_i}\right|$,

$MARE = \frac{1}{n}\sum_{i=1}^{n}\frac{|C_i - \widehat{C_i}|}{C_i}$, where C_i are actual costs of i[th] enrollee in year *t* and $\widehat{C_i}$ are predicted costs of i[th] enrollee for year *t*.

The last method is also the most broadly used approach – the evaluation of R-squared. R-squared is basically equal to: $R^2 = \frac{\sum_{i=1}^{n} \hat{y}_i - \bar{y}}{\sum_{i=1}^{n} y_i - \bar{y}}$, where $\hat{y}_i$ is predicted value of our dependent variable (predicted variance from mean costs), $\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}$ is mean of the dependent variable and y_i are real values of dependent variable. R-squared can be basically interpreted as the explained variance of dependent variable to total variance of it.

Besides the R-squared computed by the software itself when the regression is being evaluated, which is in our case the one for the annual period *t-2*, we would present also R-squared for the year *t*. It is even more desirable to see how much of the total variation in costs can be explained by the model based on the data from two years ago, because this is how the costs are predicted in practise.

By comparing profit/loss outcome, mean prediction error and R-squared before and after model modification, I should be able to verify whether the currently used model can be improved in a way I suggest or not.

5.2.1 Ex-post compensation

Before I start with the estimation itself, it is important to get back to the outliers issue. It is a common approach that there are removed observations known as outliers from the dataset. This is done so that the model is not affected by low number of values that deviate largely from the mean of the sample and so contributes undesirably into the final shape of the fitted model. However, our main aim is not to find the best fitted model, but to predict future health care costs as close to the real ones as possible. This, in our thoughts, cannot be done properly unless we keep the extreme cases in the dataset. Otherwise, the estimated costs would be very likely markedly lower than the real costs and too many cases have to be compensated ex-post what completely disrupts the meaning of ex-ante redistribution of funds. In case the insurers are aware that plenty of their enrollees would be financially supported by the state in ex-post redistribution, they would not probably care that much about efficiency. Ex-post redistribution should exist just to cover really extreme cases, not to support sickness funds in perverse incentives behaviour. Therefore, when

estimating risk indices, we would not perform data clearing and keep all the observations of year *t-2*.

Actually, dealing with outliers is very important in year *t*. As was already mentioned before, it is crucial to set the line above which the insurers are provided additional ex-post financial support, so that it would help them cover huge losses on the one hand, but on the other hand to still preserve their efficiency. Because I would not be provided with historical data going back to years *t-3* and further, it is not possible to use multiple-year high costs approach described in *Literature Review*. Though, there are two more approaches left. Either I can use *boxplot* method, which would depict remote values as single points. These would be outliers lying outside the 1.5 interquartile range of the lower as well as upper quartile and they would be partly compensated ex post by the state. How much of the costs of our outliers will be subject to ex post compensation is determined later in this paper, when the estimation itself is done (in section *Results*).

The other approach is ex post cutting off the extreme costs as it is done now in reality in Slovakia. Once the risk indices are computed, there can be set a line above which 80% of insuree´s costs are additionally compensated. Remaining 20% remains to the insuree and has to be covered by the sickness fund itself. The line for ex post compensation is computed as $RI\ x\ \bar{Y}_t + 20\ x\ \bar{Y}_t$, where $\bar{Y}_t$ are overall average costs of enrollees in year t and RI is risk index of insuree´s belonging subgroup (demographic and PCG together) (Zákon Národnej rady Slovenskej republiky 2004). $\bar{Y}_t$ is normally computed over the whole Slovak population and costs of every insurance company together, anyway, for the purposes of our analysis we can count with just one insurer´s data.

After identifying our outliers/extreme cases by either of these approaches, the amount which should be additionally compensated is actually allocated over the all insurers and covered by them not the state itself. This is because the amount intended for the whole redistribution among insurers is finite. It is collected from all the insurees (in case of economic inactive also the state) and settlements among insurers have to be covered by no more than this redistribution basis. There is a certain amount from the basis intended for these extreme patients. In case it is not enough, companies which received ex ante more money than they should have after annual accounting is done, have to cover extreme cases of other companies that receive less than they were supposed to.

Although we do not have the information about other sickness funds available, we decided to deal with ex post redistribution in a way that the 80% part which should be distributed among all the insurers, would be evenly divided among all the enrollees of the insurer which provided us with the data. Of course, it means that the insurer´s all costs, even these extreme ones, have to be covered by the insurer itself, but they would be differently distributed among enrollees. Therefore, it would make more sense to evaluate profit/loss of different subgroups of the population rather than the whole insuree pool. Obviously, ex post redistribution is not done when evaluating models by mean prediction errors, as they are simply used predicted costs against actual ones, it is important part only for computation of profit/loss outcome.

6 Data

I was provided with anonymized data from one of the insurance companies in Slovakia. The year *t*, for which we would like to predict the costs is in our case year 2016. Here we have 1 439 196 observations. In year *t-2* (2014) we are provided with 1 462 527 observations, what stands for more than quarter of all enrollees in Slovakia. The data are structured in two files for each year. One contains anonymised ID of the enrollee together with the information about total annual expenditures of each of them in euros, number of days of enrolment, age, sex, payer status and classification to PCG[6] regarding the valid law (more than 180 DDD). The other file sums up drug consumption of the insurees one year before, i.e. 2013 and 2015. The file includes anonymised ID of the enrollee, ATC classification of the group of drugs and DDD within the year.

6.1 Health Care Costs

Health care costs are used to model dependent variable, which is the difference between average monthly costs of each enrollee and overall average monthly costs of the whole population of the insurer. The summary statistics of the expenditures are displayed below, in *Table 10*. It is visible that majority of health care costs should be next to nothing, as the median of the data in both years is low and accounts for no more than 200 €. Above that, when looking at the 75th quantile of 2014 and 2016, we get 470 € and 511 € respectively. It corresponds with our intuition about how distribution of health care costs usually looks like.

[6] Note that clasification to PCG is done from the drug consumption during preceding year, i.e. during year 2013 and 2015.

Table 10: Summary Statistics of Health Care Costs (in €)

YEAR	MEAN	MEDIAN	ST. DEV.	MIN	MAX
2014	619	175	2 771	0	1 323 636
2016	666	189	2 407	0	507 477

Note that the histograms for health care costs are displayed only up to frequency of 1000 persons. This adjustment makes it able to see clearly more than just first bar of the histogram, where the majority of population lies. As it was supposed cost distributions are for both years right-skewed with large tail and the highest frequency of costs near to 0, see *Figure 6* and *Figure 7*.

Figure 6: Histogram of health care costs in 2014

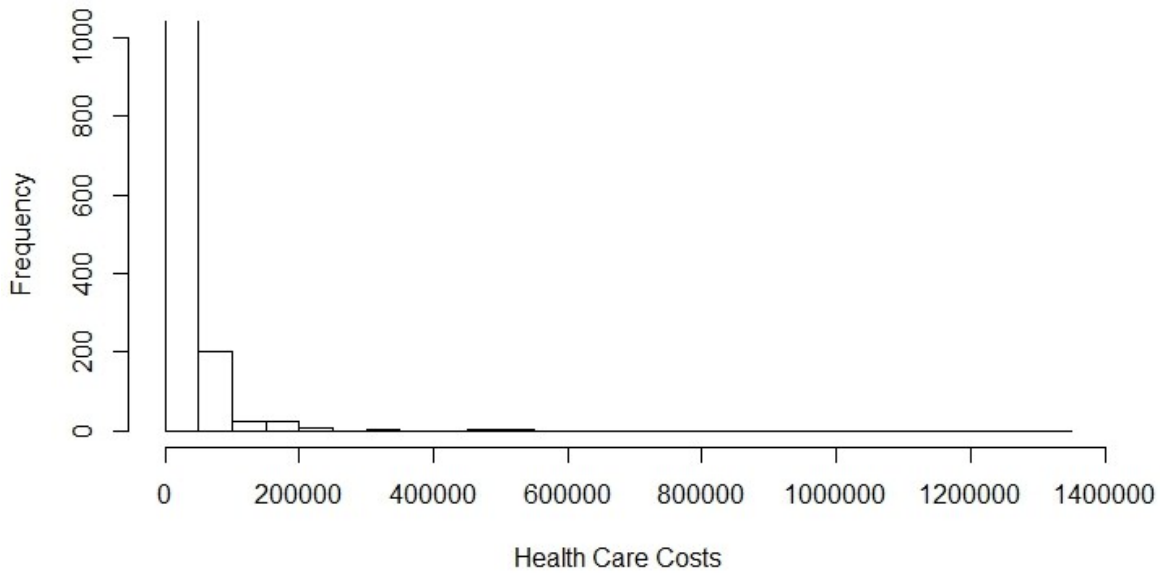
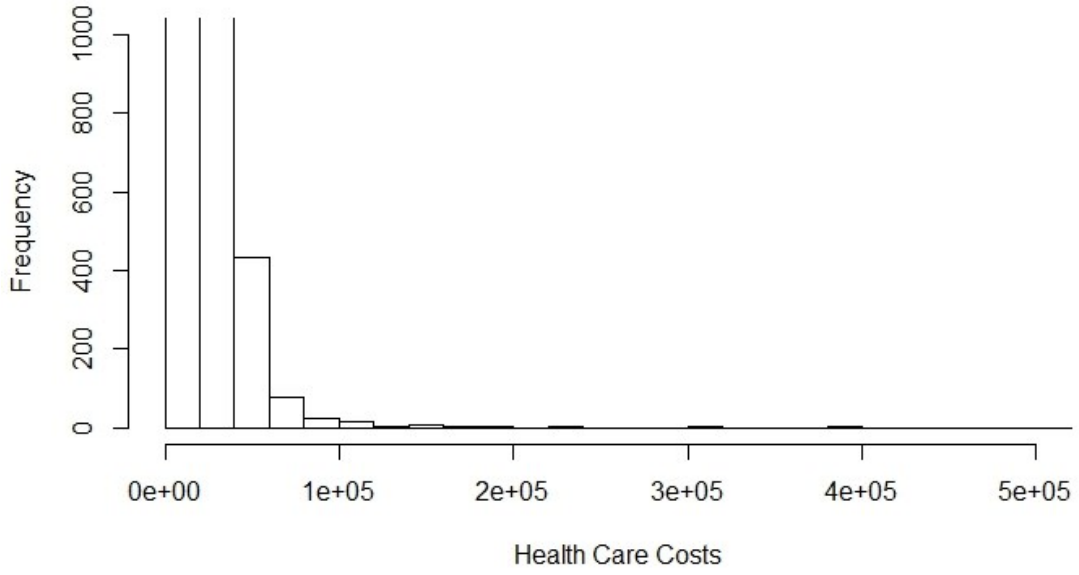


Figure 7: Histogram of health care costs in 2016



6.2 Demographic variables

Age together with gender and payer status form demographic variables of the model. Each combination of them forms one dummy variable. As there are 17 age classes – each 5 years are clustered together – for each gender and two forms of payer (either state or individual), there should be all together $17x2x2 = 68$ dummies. Actually, there are only 62, from which 61 are included into the model as was explained in *Methodology* section.

When looking at the plots of costs of different age groups for each sex displayed below, we can see that they both follow almost same pattern. Costs are higher for newborns than for older children and are increasing up to the age of 2 years old. Then they are quite stable until the age of cca 50 when it starts gradually increasing. The peak is somewhere around 80 years old, afterwards the costs drop and especially in case of women except for some small deviations are decreasing steadily. This might be explained from several views – one is that lots of people in this age are immobile and do not visit doctor as often as before. Secondly, they may be already unable to express what bothers them and so are cured only for objective findings of the doctors. Moreover, doctors tend to prescribe for

people in so high age only necessary medications. And lastly, there is a subgroup of people, who were able to reach this age because they are really healthy.

Figure 8: Age-average costs for female in 2014

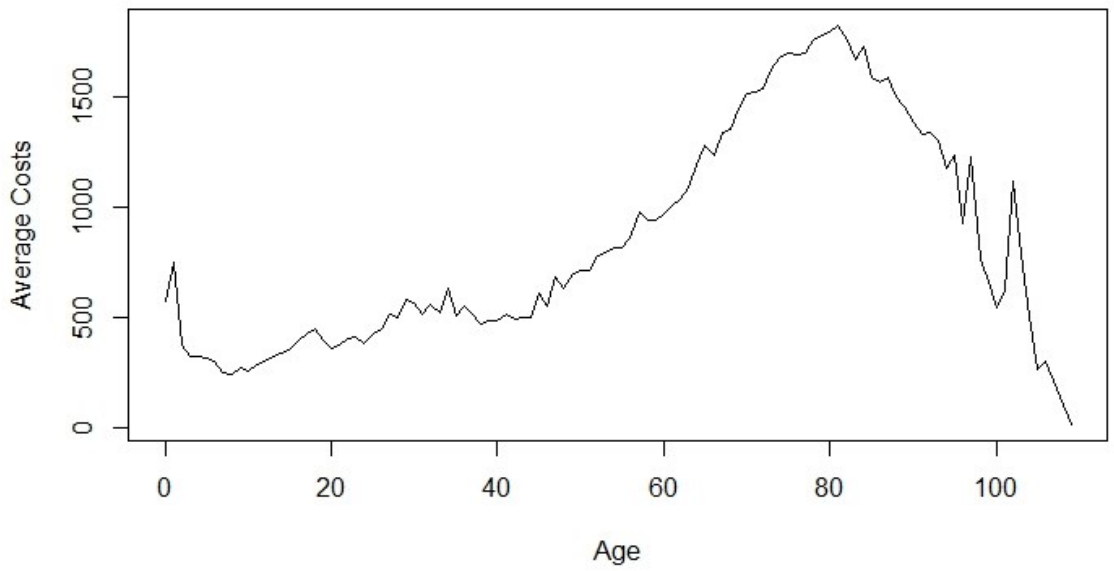
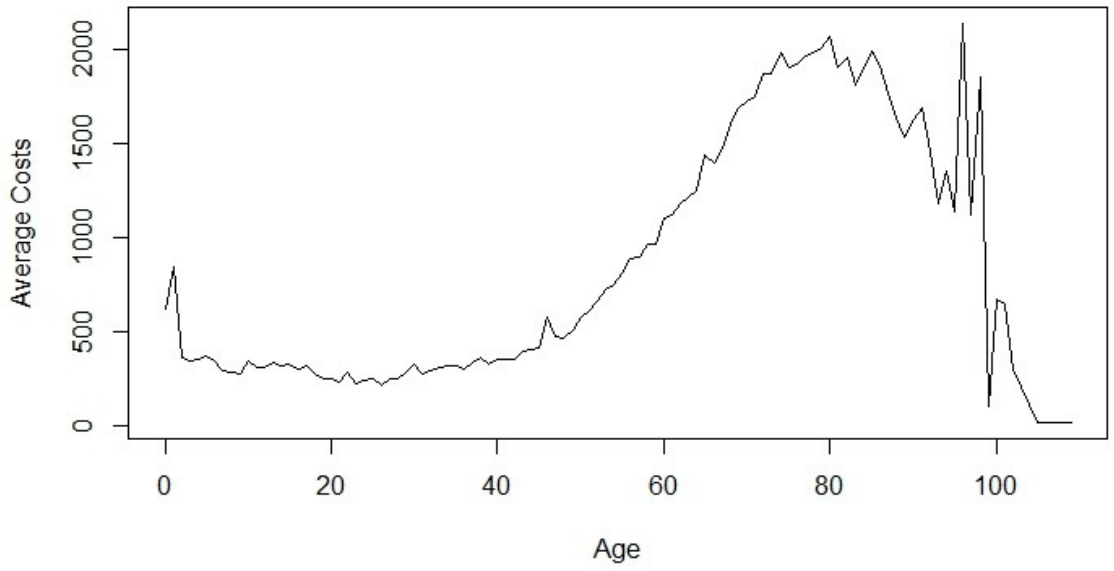


Figure 9: Age-average costs for male in 2014



The last of demographic variables indicates economic activity of the insurees. Division of the binary variable of payer status is listed in *Table 11*. We can see that in both years the share of economic inactive people forms more than 60% of the whole population of the insurer. It is not only about higher proportion of economic inactive people in the insurer´s population, but also the fact that their average monthly costs are more than twice the average monthly costs of individual payers, see *Table **12***. So, they create greater and also costlier part of the population (converted to one individual) while they are still financially supported by the state. These paid premiums therefore very likely underrate the real costs of this part of population.

Table 11: Proportion of individual and state payer status in years 2014 and 2016

YEAR	PAYER "I"	PAYER "S"
2014	557 164	905 363
2016	568 482	870 714

Note: "I" denotes individual payer, "S" state payer

Table 12: Mean of average monthly costs based on payer status in 2014 and 2016

YEAR	PAYER "I"	PAYER "S"
2014	31.94368	71.73077
2016	33.05328	79.17402

Note: "I" denotes individual payer, "S" state payer

6.3 PCGs and Drug Consumption

Drug consumption is summarized in two ways. First of all, each enrollee is classified into the PCG according to currently used principle of more than 180 DDDs consumption of the relevant drugs within 12 months and just one and the most expensive PCG rule. Above that we are provided with files containing information about more detailed medication consumption for one specific PCG – *hypercholesterolemia* (CHO). The file contains all ATC groups with DDDs for each insuree. Thanks to that we are capable to either lower threshold for assignment of person to CHO PCG or to create several DDD subgroups for this PCG. We are provided with CHO ATC consumption of enrollees who were insured in our insurance company in both years – *t-2* as well as *t.* Otherwise, we would anyway eliminate the others.

ATC classification for each PCG is summarized in *Table 13*. For classification of an enrollee into PCG consumption of all relevant ATC groups is summed up. Hence if it is usual practise to prescribe combination of several drugs at once to cure certain disease, one can quite easily reach 180 DDDs. This is due to the fact that at one visit a patient is usually prescribed drug for three months, what corresponds to 90 DDDs. In that case, lowering of this threshold would not improve the model, because one prescription still might not indicate regular patient with severe disease. We would like to check whether this is not the case of patients consuming ATC groups for CHO.

Table 13: PCGs with their ATC groups for year 2016

NUMBER	CODE	NAME	ATC GROUP
1	*AST*	*Asthma*	R03 except (R03AC18, R03AK03, R03BB, R03BC01, R03CC13, R03CC02)
2	*CFP*	*Cystic fibrosis or pancreatic exocrine disease*	J01GB01, J01XB01, R05CB13
3	*CNS*	*Brain and spine disorders*	L03AB07, L03AB08, L03AX13, L04AA23, M03BX01
4	*COP*	*Chronic obstructive pulmonary disease and severe asthma*	R03AC18, R03AK03, R03BB
5	*CRO*	*Crohn's disease, ulcerative colitis*	A07EA06, A07EC02
6	*DEP*	*Treatment with antidepressants*	N06A except (N06AA09, N06AX21)
7	*DM1*	*Type I diabetes*	A10A
8	*DM2*	*Type II diabetes*	A10B
9	*DMH*	*Diabetes with hypertension*	(A10A and at the same time [C02 except (C02KX), C03 except (C03CA01), C07, C08 except (C08CA06), C09]) or (A10B and at the same time [C02 except (C02KX), C03 except (C03CA01), C07, C08 except (C08CA06), C09])
10	*EPI*	*Epilepsy*	N03 except (N03AX12, N03AX16, N03AE01)

11	*HIV*	*HIV/AIDS*	J05AE, J05AF except (J05AF07, J05AF08, J05AF10, J05AF11), J05AG, J05AR, JO5AX except (J05AX05)
12	*CHO*	*Hypercholesterolemia*	C10 except (C10AC01, C10BX03)
13	*KVS*	*Heart disease*	C01A, C01B, C01D, C01EB15, C01EB17, C03CA01
14	*ONK*	*Malignancy*	L01 except (L01BA01), L03AA, L04AX04
15	*PAR*	*Parkinson's disease*	N04B
16	*PSY*	*Antipsychotics, Alzheimer's disease, addiction treatment*	N05A except (N05AL03, N05AN01), N06DA, N06DX01, N07BB, N07BC51
17	*RAS*	*Growth hormone therapy*	H01AC01
18	*REN*	*Renal failure*	B03X, V03AE
19	*REU*	*Rheumatic diseases treated differently as with TNF inhibitors*	A07EC01, L01BA01, L04AA13, L04AX03, M01CB01, M01CC01, P01BA02
20	*TNF*	*Rheumatic diseases treated with TNF inhibitors*	L04AA11, L04AA24, L04AB, L04AC except (L04AC05)
21	*TRA*	*Transplants*	L04AA06, L04AA10, L04AA18, L04AD01, L04AD02
22	*HOR*	*Hormonal oncology*	L02
23	*NPP*	*Neuropathic pain*	N01BX04, N03AX12, N03AX16
24	*HEM*	*Hemophilia*	B02BD except B02BD01
25	*THY*	*Thyroid disorders*	H03A, H03B

Source: Vyhláška Ministerstva zdravotníctva SR 2015b

I summarized how many out of all the people who consumed at least 1 DDD in years 2013 and 2015 were prescribed the combination of more than one medication. Moreover, there are identified people whose consumption of all drugs was maximally 180 DDDs. These could cause potential problem for the analysis, because the sum of their drug

consumption might afterwards exceed the threshold, while they could attend the doctor only once. We can see that in both years these people account for only 2% of all who consumed some CHO ATC. What is more, there are counted also individuals who were prescribed something between 90 and 180 DDDs and these are supposed to be not just "accidental" prescriptions. Therefore, we might conclude that lowering DDD or creating levels of DDD still could improve the RE modelling.

Table 14: Individuals with combination of more CHO ATC

		COMBINATION OF 2	COMBINATION OF 3	COMBINATION OF 4	ALL ≥ 1 DDD
2013	*SUM*	14 038	1 041	-	132 451
	All ≤ 180 DDD	2 949	208	-	
2015	*SUM*	10 644	760	31	122 858
	All ≤ 180 DDD	2 274	164	8	

7 Results

7.1 Model estimation

Due to the fact that each person can be assigned to no more than one PCG, when lowering threshold to 121 DDDs, there are appearing some people who were according to 181 DDDs assigned to some PCG other than CHO (which was in that time the most expensive PCG for them) and now belong to CHO as well. As we are not aware of how the cost severity of PCGs was stated for each year, but we know the steps of the process, we would simulate it. Although, because we know only the most expensive PCG of each person and official process for the purpose of stating costs severity of PCGs assigns everyone to each PCG with more than 181 DDDs, we would mimic just simpler version of it. We would keep these people in both PCGs, the costliest one according to 181 DDDs and newly assigned CHO with 121 DDD threshold, estimate the costs indices, compare them to one another, keep just the PCG with higher index and reestimate the model with just "true" PCG also for these enrollees.

After performance of this auxiliary regression it becomes obvious that costs severity of PCGs did not change compared to our initial regression. In other words, CHO remains the second cheapest PCG after HEM. Note that HEM in nationwide costs indices represents the most expensive group. However, this is exactly why we do not compare results of our estimates with officially computed ones – population of our insurer is healthier than the whole Slovak population. In fact, there are only two persons assigned to HEM PCG. This does not mean that as our results are in some aspects diametrically different, they are useless. We are not that much interested in the magnitude of the costs indices of the groups, but in improving the predictive accuracy of the model and so the profit or loss of the insurer. And this can be done when looking at just population of one insurer as well, even though the indices of the insurer differ from the nationwide ones. Anyway, this regression suggests that unless the person who now belongs to two PCGs was initially assigned to HEM PCG we keep the PCG classification provided by the insurer

and do not change it to CHO. Naturally, people who were not assigned to any PCG and should now be in CHO, would be classified that way.

Previously described procedure is applied also when instead of lowering the threshold we create new model with levels for CHO – 91-120 DDDs, 121-180 and 181 and more. We end up with similar results, where CHO levels become the second cheapest groups after HEM. Again, we assign persons first into one PCG other than any of CHO levels (unless the person was initially in HEM) or into some of the appropriate level in case he/she had no PCG before. Estimated variables of all three models are depicted in *Table 15*.

Table 15: Estimated variables

VARIABLE	ESTIMATE OF DEFAULT MODEL	ESTIMATE OF 121 CHO	ESTIMATE OF LEVELS OF CHO
INTERCEPT	-1.485	-1.485	-1.4859
FI 15-19	-22.334 .	-22.337 .	-22.3390 .
FI 20-24	-33.346 ***	-33.357 ***	-33.3592 ***
FI 25-29	-29.141 ***	-29.155 ***	-29.1602 ***
FI 30-34	-24.041 ***	-24.073 ***	-24.0789 ***
FI 35-39	-26.186 ***	-26.223 ***	-26.2348 ***
FI 40-44	-27.719 ***	-27.804 ***	-27.8280 ***
FI 45-49	-24.479 ***	-24.641 ***	-24.6904 ***
FI 50-54	-21.620 ***	-21.917 ***	-22.0308 ***
FI 55-59	-21.457 ***	-21.919 ***	-22.1108 ***
FI 60-64	-16.821 ***	-17.380 ***	-17.6335 ***
FI 65-69	8.993	8.451	8.1769
FI 70-74	2.268	1.330	0.9138
FI 75-79	-29.678	-30.788	-31.0617
FI 80≤	-17.206	-17.220	-17.3771
MI 15-19	-44.333 ***	-44.333 ***	-44.3327 ***
MI 20-24	-40.036 ***	-40.043 ***	-40.0454 ***
MI 25-29	-40.167 ***	-40.188 ***	-40.1899 ***
MI 30-34	-38.866 ***	-38.912 ***	-38.9178 ***
MI 35-39	-37.539 ***	-37.637 ***	-37.6504 ***
MI 40-44	-36.395 ***	-36.546 ***	-36.5934 ***
MI 45-49	-33.946 ***	-34.195 ***	-34.2629 ***
MI 50-54	-29.407 ***	-29.720 ***	-29.8346 ***
MI 55-59	-25.516 ***	-25.890 ***	-26.0593 ***
MI 60-64	-14.502 ***	-14.904 ***	-15.1293 ***
MI 65-69	12.392 .	12.065 .	11.7895 .
MI 70-74	26.078 *	25.399 *	25.1519 *
MI 75-79	40.012 .	39.840 .	39.3927 .
MI 80≤	471.138 ***	471.119 ***	470.7472 ***

FS 0-4	-4.072 *	-4.072 *	-4.0719 *
FS 5-9	-32.849 ***	-32.850 ***	-32.8514 ***
FS 10-14	-31.818 ***	-31.822 ***	-31.8232 ***
FS 15-19	-22.809 ***	-22.813 ***	-22.8174 ***
FS 20-24	-22.412 ***	-22.418 ***	-22.4234 ***
FS 25-29	-6.457 ***	-6.472 ***	-6.4754 ***
FS 30-34	-2.123	-2.142	-2.1521
FS 35-39	-7.381 ***	-7.423 ***	-7.4426 ***
FS 40-44	-5.762 *	-5.846 *	-5.8844 *
FS 45-49	11.855 ***	11.692 ***	11.6140 ***
FS 50-54	25.251 ***	24.970 ***	24.8133 ***
FS 55-59	22.020 ***	21.576 ***	21.3249 ***
FS 60-64	5.719 **	5.152 **	4.8540 **
FS 65-69	15.027 ***	14.441 ***	14.0652 ***
FS 70-74	29.895 ***	29.316 ***	28.9090 ***
FS 75-79	37.460 ***	36.970 ***	36.5846 ***
FS 80≤	46.741 ***	46.365 ***	46.0659 ***
MS 5-9	-29.958 ***	-29.960 ***	-29.9623 ***
MS 10-14	-30.155 ***	-30.160 ***	-30.1622 ***
MS 15-19	-32.894 ***	-32.899 ***	-32.9010 ***
MS 20-24	-35.159 ***	-35.169 ***	-35.1734 ***
MS 25-29	-32.023 ***	-32.045 ***	-32.0532 ***
MS 30-34	-18.427 ***	-18.477 ***	-18.4817 ***
MS 35-39	-17.030 ***	-17.095 ***	-17.1292 ***
MS 40-44	-9.727 ***	-9.823 ***	-9.8861 ***
MS 45-49	13.098 ***	12.940 ***	12.8631 ***
MS 50-54	43.739 ***	43.513 ***	43.3821 ***
MS 55-59	55.204 ***	54.876 ***	54.6845 ***
MS 60-64	36.526 ***	36.117 ***	35.8912 ***
MS 65-69	40.102 ***	39.662 ***	39.3764 ***
MS 70-74	56.282 ***	55.881 ***	55.5565 ***
MS 75-79	67.834 ***	67.420 ***	67.0796 ***
MS 80≤	75.899 ***	75.568 ***	75.3201 ***
AST	58.669 ***	58.931 ***	59.0773 ***
CFP	1663.100 ***	1663.135 ***	1663.1519 ***
CNS	1016.352 ***	1016.564 ***	1016.6841 ***
COP	158.963 ***	159.362 ***	159.6196 ***
CRO	126.398 ***	126.626 ***	126.7483 ***
DEP	43.780 ***	44.060 ***	44.2139 ***
DM1	196.423 ***	196.806 ***	197.0461 ***
DM2	45.010 ***	45.392 ***	45.6113 ***
DMH	58.827 ***	59.271 ***	59.5448 ***
EPI	92.077 ***	92.244 ***	92.3358 ***
HIV	820.610 ***	820.784 ***	820.8643 ***
CHO	25.782 ***	-	-
CHO121	-	24.875 ***	-
CHO 91-120	-	-	17.2183 ***

CHO 121-180	-	-	17.4898 ***
CHO 181 AND MORE	-	-	26.4798 ***
KVS	109.315 ***	109.753 ***	110.0533 ***
ONK	1196.547 ***	1196.934 ***	1197.1664 ***
PAR	170.941 ***	171.362 ***	171.6604 ***
PSY	101.721 ***	101.970 ***	102.1231 ***
RAS	707.683 ***	707.697 ***	707.7039 ***
REN	2485.863 ***	2486.237 ***	2486.4840 ***
REU	110.137 ***	110.492 ***	110.6951 ***
TNF	1113.028 ***	1113.269 ***	1113.3920 ***
TRA	413.747 ***	414.013 ***	414.1569 ***
HOR	197.519 ***	197.946 ***	198.2206 ***
NPP	170.040 ***	170.433 ***	170.6751 ***
HEM	9.940	9.971	9.9859
THY	NA	NA	NA
R-SQUARED	0.1223	0.1223	0.1223

*Note: significance codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1, ' ' 1*

Apparently, there is no person belonging to THY PCG in the dataset and so no estimate for the group is provided[7]. What is more, HEM is the only PCG which is not statistically significant. It is very probably because of the fact that there are only two people assigned to this group. All the others are always statistically different from zero on 0.1% significance level. Speaking about demographic variables, majority of them is also strongly significant, there are just some age groups which are not. Of course, we cannot omit these variables from the models. Nor would I group them into differently gathered age groups, as this is not the aim of my thesis – it is to show whether differently set PCG groups do matter, not the demographic ones. Otherwise it would probably make sense also to isolate the newborns from the first clustered age group, as was done by Hajíčková (2015) in her thesis. Argumentation behind this is that newborns tend to be more sensitive to get ill than children in 1-4 years. In our models the groups with lowered statistical significance or those that are not significant at all are groups of individual payers in higher age. This is indeed caused by the fact that there are only very few of elderly people who are still economic active. For instance, there are only 37 men above the age of 79 classified to be individual payers in year *t-2*. In case of women there are just 8 of them. We believe that the higher age groups should be no longer divided between individual and state payer

[7] Consequently 16 069 observations from year t (2016) that were assigned to THY PCG are deleted. We do not have an estimate nor the cost index for this subgroup, so we are not able to correctly estimate their future health care costs.

categories. Anyway, we would like to keep the logic for determination of demographic variables of the official model used in Slovakia.

When investigating R-squared of the models, which tells us basically how much of the total variance of the dependent variable is explained by our explanatory variables, we can see that the models are able to catch more than 12% of the variance in health care costs. But we can see the coefficient of determination is not changing at all. This, however, still does not mean the adjusted models do not lead to better profit/loss situation of the insurer. Actually, it accurately describes the fact that we are investigating just one specific subgroup of enrollees and that the enrollees of the insurer are quite healthy, as there are only around 58 000 people assigned to original CHO PCG. Above that this is still the performance within the year of estimation, while we are interested in ability to predict costs two years later. Therefore, we would later take a look on profit/loss and mean prediction errors.

The intercept represents the reference group, which is omitted from the variables – man aged between 0 and 4 years (and with the state as premium payer, which is always that way for this age) without any PCG. It moves around -1.49 in all models indicating that this group has lower average monthly costs compared to the insurer´s population average by 1.49 €. When we want to interpret changes in average costs for other subgroups, we need to sum up all relevant coefficients, e.g. in case of original model, for men aged 50-54 who are individual payers and are assigned to ONK PCG, we get by -1.485 + (-25.516) + 1 196.547 = 1 169.55 € higher monthly average costs than population average. Most expensive demographic group are men above the age of 80, individual payers and those who are supported by the state (471.14 € and 75.9 € respectively). The cheapest are economic active men between 15 and 19 years (-44.33 €).

Renal failure was computed solidly as the most expensive PCG (2 485.86 €). Together with cystic fibrosis, malignancy, TNF rheumatic diseases and brain and spine disorders they cross 1000 € line in case of all estimated models. As in the case of abovementioned auxiliary regressions, hypercholesterolemia placed as the second cheapest chronic disease with 25.78 € in initial model and even lower estimate for 121 DDDs threshold (24.88 €). This makes perfect sense as there are included more insurees, even those with lower drug consumption and presumably also less severe state of disease. After

clustering three levels of drug consumption into three different CHO groups, we get 17.22 € for 91-120 DDDs, 17.49 € for 121-180 DDDs and 26.48€ for more than 180 DDDs. They end up all strongly statistically significant what makes us believe such a clustering could be useful measure.

7.1.1 Risk indices determination

Computed coefficients determine risk indices needed for insurer´s income simulation. Based on methodology described before, we first of all computed cost indices for all demographic as well as chronic condition subgroups from which we get risk indices summarized in *Table 16*. For individual payers, there are obviously no enrollees aged 0-14, as they are all supported by the state. Intercept from regressions represents men aged 0-4. Generally, in case the risk index for demographic factor is equal to 1, the costs of that subgroup are no different from the population mean costs. As PCG group cannot exist without demographic group, PCGs are just addings to demographic risk indices.

To make the results more illustrative it is perhaps better to include graph instead of table. However, as the differences of risk indices across the models are small in magnitude, these variations are not very visible. Anyway, generally speaking all the demographic RI are smaller for our modified models than in case of the initial one (except three cases where they are equal for initial model and 121 CHO model). On the other hand, in case of the PCG cost indices the situation is vice versa. This suggest that in modified models there are higher weights put on the chronic conditions of the enrollees to the detriment of demographic risk indices.

Table 16: Demographic and PCG risk indices of estimated models

VARIABLE	RI INITIAL MODEL	RI 121 CHO MODEL	RI CHO LEVELS MODEL
FI 0-4	-	-	-
FI 5-9	-	-	-
FI 10-14	-	-	-
FI 15-19	0.578972	0.578919	0.578868
FI 20-24	0.384323	0.384129	0.384074
FI 25-29	0.458651	0.458404	0.458296
FI 30-34	0.548799	0.548234	0.548113
FI 35-39	0.510884	0.51023	0.510005

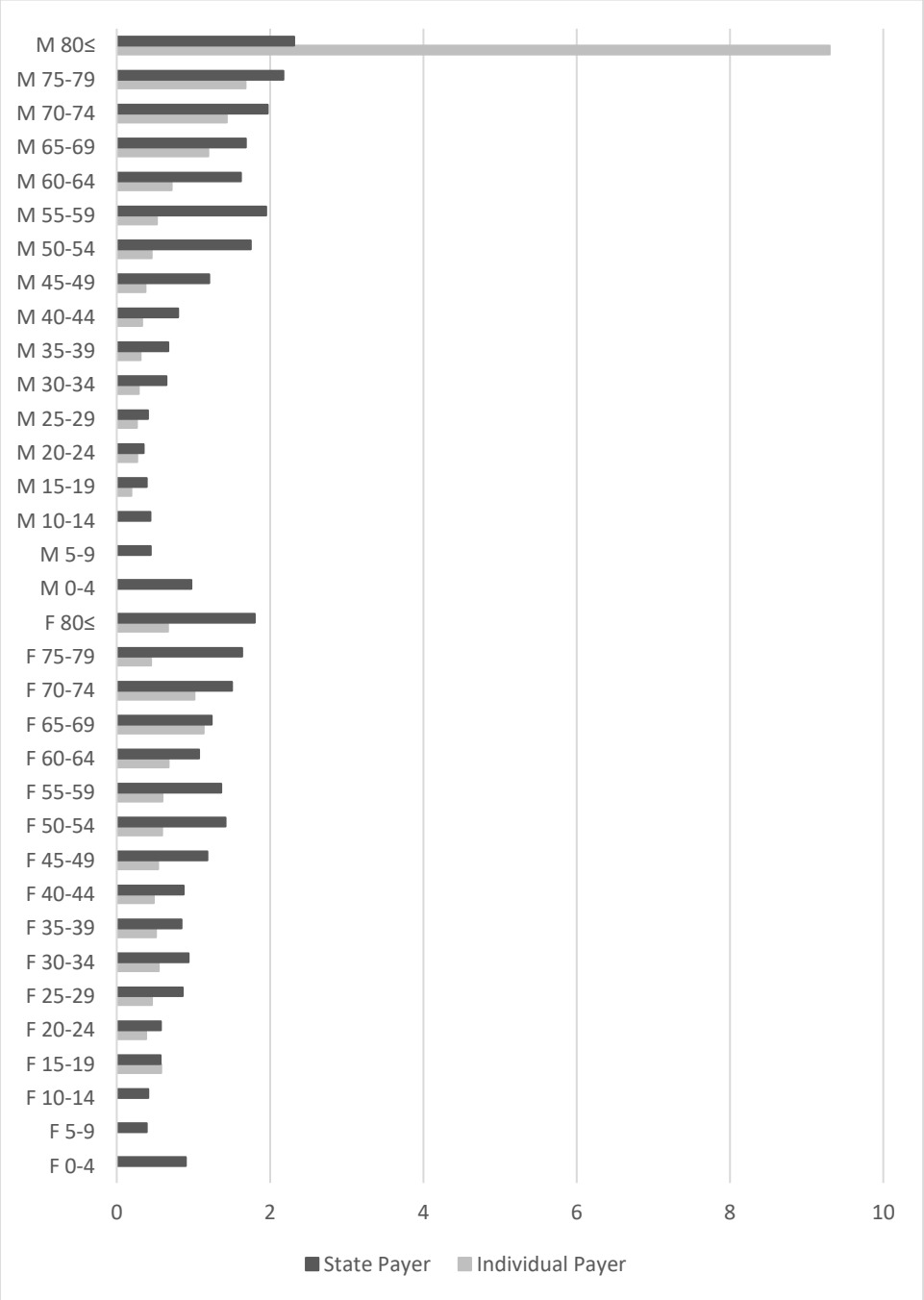
FI 40-44	0.483786	0.482284	0.481844
FI 45-49	0.541057	0.538194	0.537304
FI 50-54	0.591593	0.586343	0.584316
FI 55-59	0.594474	0.586308	0.582902
FI 60-64	0.676421	0.66654	0.662043
FI 65-69	1.132712	1.123132	1.118271
FI 70-74	1.01384	0.99726	0.989887
FI 75-79	0.449159	0.429538	0.424685
FI 80≤	0.669616	0.669368	0.666575
MI 0-4	-	-	-
MI 5-9	-	-	-
MI 10-14	-	-	-
MI 15-19	0.190115	0.190115	0.190105
MI 20-24	0.26607	0.265946	0.265888
MI 25-29	0.263754	0.263383	0.263333
MI 30-34	0.286751	0.285938	0.285819
MI 35-39	0.310207	0.308475	0.308222
MI 40-44	0.330428	0.327759	0.326906
MI 45-49	0.373717	0.369316	0.3681
MI 50-54	0.453949	0.448417	0.446375
MI 55-59	0.522727	0.516116	0.513108
MI 60-64	0.717412	0.710306	0.706308
MI 65-69	1.192793	1.187013	1.182128
MI 70-74	1.434709	1.422707	1.418323
MI 75-79	1.681008	1.677968	1.670045
MI 80≤	9.301644	9.301309	9.294721
FS 0-4	0.901774	0.901774	0.90176
FS 5-9	0.393108	0.39309	0.39305
FS 10-14	0.411332	0.411261	0.411224
FS 15-19	0.570576	0.570506	0.570412
FS 20-24	0.577594	0.577488	0.577376
FS 25-29	0.859616	0.859351	0.859275
FS 30-34	0.936225	0.935889	0.935694
FS 35-39	0.843283	0.842541	0.842179
FS 40-44	0.871901	0.870416	0.869722
FS 45-49	1.183301	1.18042	1.179026
FS 50-54	1.420091	1.415124	1.412338
FS 55-59	1.362979	1.355131	1.350677
FS 60-64	1.074841	1.064818	1.059535
FS 65-69	1.23937	1.229012	1.222353
FS 70-74	1.502179	1.491944	1.484734
FS 75-79	1.635899	1.627237	1.620409
FS 80≤	1.799951	1.793304	1.788002
MS 0-4	0.973751	0.973751	0.973735
MS 5-9	0.44421	0.444174	0.444118
MS 10-14	0.440727	0.440639	0.440584
MS 15-19	0.392313	0.392224	0.392173

MS 20-24	0.352276	0.352099	0.352006
MS 25-29	0.407708	0.40732	0.407159
MS 30-34	0.648033	0.647149	0.64705
MS 35-39	0.672727	0.671578	0.670957
MS 40-44	0.801815	0.800118	0.798987
MS 45-49	1.205273	1.20248	1.201105
MS 50-54	1.746887	1.742892	1.740562
MS 55-59	1.949544	1.943746	1.940345
MS 60-64	1.619389	1.61216	1.608152
MS 65-69	1.682599	1.674821	1.669757
MS 70-74	1.968599	1.96151	1.955759
MS 75-79	2.172793	2.165475	2.159442
MS 80≤	2.315351	2.3095	2.305102
AST	1.03704	1.041672	1.044258
CFP	29.39716	29.39778	29.39808
CNS	17.96516	17.96891	17.97103
COP	2.80985	2.816902	2.821456
CRO	2.234227	2.238257	2.240419
DEP	0.773861	0.77881	0.78153
DM1	3.471997	3.478767	3.483011
DM2	0.795602	0.802355	0.806231
DMH	1.039833	1.047682	1.052521
EPI	1.627564	1.630516	1.632139
HIV	14.5052	14.50828	14.5097
CHO	0.455726	-	-
CHO121	-	0.439694	-
CHO 91-120	-	-	0.304353
CHO 121-180	-	-	0.309152
CHO 181 AND MORE	-	-	0.46806
KVS	1.932265	1.940008	1.945316
ONK	21.15031	21.15715	21.16126
PAR	3.021574	3.029016	3.03429
PSY	1.798033	1.802434	1.805141
RAS	12.50909	12.50934	12.50946
REN	43.94042	43.94703	43.9514
REU	1.946795	1.95307	1.95666
TNF	19.67402	19.67828	19.68045
TRA	7.313443	7.318145	7.320689
HOR	3.49137	3.498918	3.503772
NPP	3.005648	3.012595	3.016874
HEM	0.175701	0.176249	0.176512
THY	NA	NA	NA

Clearly, as the higher estimates were for men aged +80, this one must hold in case of risk indices too, see

*Figure **10***. Figure depicts that in most of the cases, apart from +80 men and women between 15 and 19 years, economic inactive people are more expensive in terms of the health care costs. This might have several reasons – either they are not used to preventive visits of doctor and consequently get more seriously ill or on the other hand there are included individuals who are economic inactive as they are handicapped and disabled persons and pensioners who need health care more often and to a greater extent.

Figure 10: Demographic risk indices for initial model



7.2 Models comparison

7.2.1 R-squared

R-squared as a proportion of explained variance to the total variance of our dependent variable was already evaluated for year *t-2*. However, we are perhaps even more interested in how much of the total variance of the costs in year *t* are explained by our model. Therefore, we include also R-squared computed for the year 2016 in *Table 17*. Clearly the number rises with the models, suggesting that our modified models are able to capture even more information than the currently used model in practise. Even that the percentage values do not vary massively (improvement from initial model to either of our modified models is cca 0.2%), nor was it expected, it is confirmed by the theory that the risk equalization models are not able to predict more than 20% of the variation in people´s health care costs (van Vliet 1992). Everything else is considered to be a matter of coincidence. Therefore, we can say that the performance of all of these models is above expectations and so even small improvements can be considered as very successful.

Table 17: R-squared for year t (2016)

	INITIAL MODEL	121 CHO MODEL	CHO LEVELS MODEL
R-SQUARED	0.14913	0.1513	0.15132

7.2.2 MAPE and MARE

In *Table 18* and *Table 19* are summarized results for mean prediction errors of several insurer´s population subgroups and for each model. Because the model modifications were done just on one specific subgroup of enrollees (those with CHO ATC consumption), the changes in MAPE and MARE are small in magnitudes. What is more, as in Slovakia, each person can be added just to one PCG, even after creating lower thresholds for CHO assignment, the predictive power of the model changes just slightly.

We can see that unfortunately it seems that our intuition in adjusting the PCG classification does not bring any improvement. Still it is crucial to notice that the differences in mean absolute errors are not larger than two euros. In addition, this is just an expression of the average difference between predicted and real costs. In reality, the computation of how much the insurance company receives for the patient is much more complicated than just simply predict the costs from two years old data. Because of that, we assume the evaluation of the profit/loss outcome in the next section catches the differences among our models more accurately and realistically.

Table 18: MAPE evaluation in €

WHOLE POPULATION OF 2016		
DEFAULT MODEL	*121 CHO Model*	*CHO Levels Model*
55.39666	55.42243	55.41144
CHO SUBSAMPLE (THOSE WITH AT LEAST 91 DDDS)		
DEFAULT MODEL	*121 CHO Model*	*CHO Levels Model*
86.87908	87.84329	88.28565
10% OF THE MOST EXPENSIVE ENROLLEES		
DEFAULT MODEL	*121 CHO Model*	*CHO Levels Model*
282.8843	281.1292	281.1067
10% OF THE CHEAPEST ENROLLEES		
DEFAULT MODEL	*121 CHO Model*	*CHO Levels Model*
27.72564	27.61956	27.57257

Table 19: MARE evaluation in €

WHOLE POPULATION OF 2016		
DEFAULT MODEL	*121 CHO Model*	*CHO Levels Model*
3.098502	3.094963	3.091201
CHO SUBSAMPLE (THOSE WITH AT LEAST 91 DDDS)		
DEFAULT MODEL	*121 CHO Model*	*CHO Levels Model*
1.975321	2.066826	2.098775
10% OF THE MOST EXPENSIVE ENROLLEES		
DEFAULT MODEL	*121 CHO Model*	*CHO Levels Model*
0.6409097	0.6383027	0.6381751
10% OF THE CHEAPEST ENROLLEES		
DEFAULT MODEL	*121 CHO Model*	*CHO Levels Model*
13.45719	13.40876	13.38731

7.2.3 Profit/Loss

Exactly because of more complicated real-life process for income computation as well as adjustment of annual costs for too high-costs individuals, the determined profit or loss differ much more significantly from each other than it was in case of MAPE and MARE, summed up in *Table **20***. Firstly, we applied the first method for cutting off extreme costs and it is the one used currently also in practise. There is set the threshold (described in *Methodology* section) above which 80% of the costs are additionally compensated. In reality, these costs are distributed among all the insurance companies in Slovakia based on coefficients determining which insurer has higher proportion of extreme costs patients

Our insurer appears in all cases of the analysis when the whole population is taken in red numbers. Anyway, the rising tendency in favour of the adjusted models cannot be overlooked. But due to the fact that even extreme costs are still covered solely by our insurer, just differently distributed, the results for whole population cannot be excessively distinct. The differences would be more visible What makes more sense is to take into consideration several specific subpopulation, where the differences have higher explanatory power.

When talking about subgroups, we can see that the 10% of the least costly enrollees make profit, which is lower for our adjusted models. But it is essential to realize that these profits are made to the detriment of other subgroups, like the 10% of the most expensive people or subgroup of CHO patients, where the insurer appears in red numbers. Therefore, it is not so advantageous when the profit of one subgroup rises extremely and so even if the initial model shows the highest profit for 10% of the cheapest enrollees, it cannot be taken as the best model.

We should also consider the 10% of the most expensive individuals, we can see the lowering tendency in favour of our adjusted models, mostly CHO levels model. It is exactly the case that even if this model has the lowest profit for 10% of the least expensive enrollees, it has also the lowest loss for the 10% of the most expensive ones. This means that the distribution of income is better designed in CHO levels model than in the other two

models. Still the 121 CHO model has also better results for this subgroup than the initial model based on the real model used in practise.

For us the most notable subgroup is the one with those who are assigned to CHO PCGs. The group is created so that the models are comparable (there are enrollees with more than 90 DDDs for CHO ATC consumption). Each of our three models end up in loss, what may suggest that people who consume more than 90 DDDs are not sufficiently compensated by neither of the models. However, the results get better with 121 CHO and even less money are lost for the subgroup when CHO levels model is taken. This probably means that even persons with lower than 91 DDDs consumption of CHO ATC drugs should be somehow compensated more than just by demographic adjusters. Of course, in case of the people with at least some consumption of relevant PCG drugs there is much higher probability that they suffer from some other chronic disease as well, what may contribute to their overall costs markedly. Still the Slovak system does not offer multiple PCG assignment at this time.

Table 20: Profit/Loss evaluation (after classic ex-post compensation) in €

WHOLE POPULATION OF 2016		
DEFAULT MODEL	*121 CHO MODEL*	*CHO LEVELS MODEL*
- 1 768.94	- 1 288.12	- 1 288.28
CHO SUBSAMPLE (THOSE WITH AT LEAST 91 DDDS)		
DEFAULT MODEL	*121 CHO MODEL*	*CHO LEVELS MODEL*
- 2 568 477.00	- 1 122 251.00	- 337 110.00
10% OF THE MOST EXPENSIVE ENROLLEES		
DEFAULT MODEL	*121 CHO MODEL*	*CHO LEVELS MODEL*
- 296 027 147.00	- 295 929 625.00	- 295 862 389.00
10% OF THE CHEAPEST ENROLLEES		
DEFAULT MODEL	*121 CHO MODEL*	*CHO LEVELS MODEL*
42 764 642.00	42 610 629.00	42 542 927.00

7.2.3.1 Boxplot method

When instead of using the threshold officially set by the law we apply boxplot method to identify outliers, the upper threshold is set to 1 143.66 €. All the annual health 178 831 observations above the threshold (more than 12% of the data). The part of the costs of these outliers should be now additionally compensated. The question is how to set the percentage share of the costs which would be ex post compensated. Then the process is as before – these costs are evenly distributed among every insuree and we are interested in how the profit/loss behaves for different subgroups of the population. We tried to set the percentage line differently (also 80% as it is in the traditional method) and find out that 65% of additional compensation brings the best results for the investigated groups, see *Table 21*.

Clearly the overall costs are identical for boxplot method as well as for threshold method used before, as the income does not change and costs are just differently distributed in the population. The subgroups though have completely discrepant results. All of them show profit in case of each model. But the initial model puts lower weight on CHO subsample (what was expected) and higher on 10% of the cheapest insurees. This can be viewed as undesired characteristics. The cheapest population is not the main target for improving profit/loss outcome. The improvement in comparison to previous method can be seen for both of the groups with higher costs demand, as they are no longer undercompensated. However, we have to conclude that the boxplot approach strongly overrates these groups, what is a consequence of the fact that the method cuts 65% of costs of each outlier. This means that the costlier the patient the greater his/her ex post compensation.

Table 21: Profit/Loss evaluation (boxplot method) in €

WHOLE POPULATION OF 2016

DEFAULT MODEL	*121 CHO MODEL*	*CHO LEVELS MODEL*
- 1 768.94	- 1 288.12	- 1 288.28

CHO SUBSAMPLE (THOSE WITH AT LEAST 91 DDDS)

DEFAULT MODEL	*121 CHO MODEL*	*CHO LEVELS MODEL*
7 929 657.00	9 381 231.00	10 169 597.00

10% OF THE MOST EXPENSIVE ENROLLEES

DEFAULT MODEL	*121 CHO MODEL*	*CHO LEVELS MODEL*
12 766 236.00	12 863 712.00	12 930 853.00

10% OF THE CHEAPEST ENROLLEES

DEFAULT MODEL	*121 CHO MODEL*	*CHO LEVELS MODEL*
5 268 702.00	5 114 693.00	5 047 002.00

8 Discussion and Conclusion

Optimizing the risk equalization models was proven to be the best mechanism to improve efficiency and so as well competition among sickness funds. Currently used PCG model in Slovakia shows stronger improvement compared to previously used demographic one. Though we believe there is still space for enhancement. In our analysis we successfully confirmed that the currently used risk equalization model in Slovakia can be improved in both ways suggested. Either the threshold for assignment of the person into the PCG can be lowered (from currently used 181 DDDs to for example 121 DDDs) in order to include also those who even if consume less drugs, in our opinion their health condition cannot be predicted based on pure demographic risk adjusters. Or there might be created several PCG subgroups, i.e. different DDD levels (we suggested consumption of 91-120 DDDs, 121-180 DDDs and more than 180 DDDs).

Profit/loss of the insurer got better in both cases. Model with 121 DDDs threshold lowered the loss over CHO subsample by almost million and half euros and 10% of most expensive enrollees by almost 100 000 €. Even stronger results showed the model with several DDD levels for the CHO PCG, where the CHO group compensation improved by additional 785 000 € and 10% costliest people by 67 000 € compared to 121 DDDs model. Positive outcomes have also alternative approach with boxplot. However, this method is not applied in practise and should be more deeply revised to set the threshold for ex-post compensation properly.

Apart from the profit/loss analysis we conducted also comparison of R-squared of the models. The results support our hypothesis when the value of R-squared rised from initial model´s 14.9% to 15.1% of both of our modified models. Our research is based on real data and large enough sample to believe that these kinds of alternations in PCG classification lead to better designed risk adjustment model.

We are convinced that the alternative PCG models described and analysed in this work can create better environment for health insurers and consequently improve competition among them. The better the risk adjustment is set, the more efficient the sickness funds are. This finally creates more equal surroundings also for insurees, who are

no longer subject to selection from insurer´s side. Application of these models in real life is costless as all the necessary information are already available.

For further analysis we suggest creating these models for each PCG and ideally use data for the whole Slovak population. This kind of analysis may show the differences among models more precisely. Furthermore, we believe that crucial drawback of Slovak model lies in the principle of maximally one PCG for the enrollee. An individual with several chronic diseases is strongly believed to be also riskier enrollee in terms of health care costs demand and so should be assigned to each chronic condition group based on his/her drug consumption. This restriction does not occur in the Dutch system nor in the Czech Republic, where the PCG model was introduced just this year. Additionally, what was already mentioned before are possible modifications of age groups – on the one hand newborns is supposed to be riskier subgroup of population than children between 1 to 4 years old and so should be probably separated from the first age group. Moreover, the division between economic active and inactive people in the higher age groups seems to be meaningless. Our analysis confirmed that groups of economic active people above the age of 65 showed lower significance if any at all. These groups are formed of very few individuals who tend to lose their economic active status within the short period and so should be rather clustered together with inactive individuals.

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