To what extent can risk equalization be improved with a risk adjuster based on the probability of dying?

Thesis

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Summary

Introduction

Risk-equalization models can be used to avoid incentives for risk selection. These models compensate insurers for the predictable profits they make for the low-risk enrolees and the predictable losses for the high-risk enrolees. However, risk-equalization models are imperfect. Insurers are undercompensated by these models for specific groups of enrolees. The group of enrolees with a high probability of dying, which incur high healthcare costs, might be one of these groups. If the group of enrolees with a high probability of dying is undercompensated by the current risk-equalization model, insurers make predictable losses on this group. As a result they may not contract the best quality of healthcare for treatments that are related to the final stage of life. The aim of this study is to gain insight in the predictability of dying. It will be researched to what extent insurers are financially compensated by the current risk-equalization model for the group with a high probability of dying. Furthermore, it will be studied to what extent selection incentives can be reduced by including a new variable in the risk-equalization model, the risk adjuster “yes/no high probability of dying”.

Research methods

In this study, a database of 1.3 million enrolees of a Swiss health insurer is used. A prediction model is developed to estimate the probability of dying for individuals. With this model enrolees are divided into two groups based on the probability of dying. After distinguishing the two groups, it is determined whether the current risk-equalization model is adequately compensating insurers for the group with a high probability of dying. This risk-equalization model was extended with a new risk adjuster “yes/no high probability of dying” in part 3. Three different metrics are used to evaluate these two risk-equalization models.

Results

The actual percentages of dying for enrolees who were assigned to the group with a high probability of dying are 30 times higher than for the group with a low probability of dying. This means that the prediction model performs well. It turns out that insurers are on average undercompensated by the current risk-equalization model for the group of enrolees with a relatively high probability of dying. The inclusion of the new risk adjuster “yes/no high probability of dying” in the risk-equalization model eliminates this undercompensation.

Discussion & conclusion

Enrolees with a high probability of dying are predictably unprofitable for insurers. This has consequences for the incentives for risk selection and as a result this might lead to not contracting the best quality of healthcare related to the final stage of life. Incentives for risk selection can be reduced by including a new risk adjuster, “yes/no high probability of dying”. However, there are still questions that may need to be answered before this new risk adjuster can be implemented.

Table of contents

1. Introduction

In the past decades health reforms have taken place to improve healthcare systems. Several countries in Europe, such as the Netherlands and Switzerland, developed a system called regulated competition. Regulated competition implies competition on the health insurance and the healthcare provider market. In these systems the government has assigned the individual insurers as third-party purchasers of care; the risk bearing competing insurers purchase healthcare for their enrolees. They are allowed to contract the providers selectively, whereas they are not supposed to select their enrolees (Van de Ven et al., 2003). To provide access to healthcare for everyone, health insurance is mandatory for every citizen. These citizens have the opportunity to switch from insurance company every year (De Pietro et al., 2015; Van de Ven et al., 2003).

In regulated competitive systems the government has obliged competitive insurers to accept all applicants and ask the same premium from everyone who is enrolled in their insurance plan. The intention of this community-rated premium is to create implicit cross-subsidies between low-risk and high-risk enrolees (De Pietro et al., 2015; Van de Ven & Ellis, 2000). A side effect of these community-rated premiums is that they create predictable profits and losses in healthcare expenses. These predictable profits for the low-risks and predictable losses for the high-risks give insurers incentives to select enrolees based on their risk (Van de Ven & Ellis, 2000). A risk-equalization model can be used to avoid incentives for risk selection. This system compensates the insurers for the predicted variations in healthcare expenses (De Pietro et al., 2015; Schokkaert & Van de Voorde, 2006; Van de Ven et al., 2003). However, several previous studies have found that risk-equalization models are imperfect (Layton et al., 2018; Van Kleef et al., 2013). There are groups of enrolees that are undercompensated by risk equalization (Van Kleef et al., 2013). With an imperfect risk-equalization model, insurers still have financial incentives to select the enrolees with predictably low-risk of healthcare use. By selecting these predictably profitable enrolees the efficiency and the quality of healthcare will be threatened (Van Kleef et al., 2013; Van de Ven et al., 2003).

Current risk-equalization models may not adequately compensate insurers for the group of enrolees with a high probability of dying. Previous studies have shown that healthcare costs are extremely high in the final stage of life (Polder et al., 2006; Stooker et al., 2001). That means that enrolees with a relatively high probability of dying incur high healthcare costs. If the probability of dying drive up the healthcare costs, it could be possible that the current risk-equalization model is undercompensating the insurers for that group of enrolees. As a result, insurers make predictable losses on this group and might have incentives to engage in risk selection via the purchasing of healthcare. For example, they may not contract the best quality of healthcare for usual treatments in the final stage of life. It has not previously been investigated to what extent the risk-equalization model compensates for this group and this will be researched in this study.

If insurers appear to be undercompensated for enrolees with a high probability of dying, the factor “yes/no high probability of dying” could be included in the risk-equalization model. Including this variable can improve the risk-equalization model. As a result, incentives for risk selection will decrease.

1.1. Research question

The aim of this study is to gain insight into the predictability of dying. The first objective is to identify the group of enrolees with a relatively high-risk of dying. Thereafter, this study will research to what extent insurers are adequately compensated for this group. The possibility to include the risk adjuster "yes/no high probability of dying" in the risk-equalization model allows researching to what extent such a risk adjuster improves the risk-equalization model. This leads to the following three research questions:

- To what extent is "dying" predictable using administrative information from previous years?
- To what extent are insurers financially compensated for enrolees with a relatively high probability of dying by risk equalization?
- To what extent can selection incentives be reduced by including a risk adjuster based on the probability of dying?

It turns out that it is possible to estimate the probability of dying for individuals in the dataset. In this exploratory research, the possibility of an extension of current risk-equalization models by adding a new risk adjuster will be studied. The results of this research provide important insights for further improvements of risk-equalization models in various countries.

1.2. Overview of chapters

The theoretical framework, chapter 2, discusses relevant background information about risk-equalization models, the incentives for risk selection and the potential contribution of end-of-life spending to these incentives for risk selection. In chapter 3, the method section is presented. In this chapter the dataset and the different parts of this research are described. The results of this study are showed in chapter 4. In the last chapter of this research the strengths and limitations will be discussed. Recommendations for further research and a conclusion are also included in this chapter.

2. Theoretical framework

2.1. The risk-equalization model

In regulated health insurance markets, insurers are typically forced to accept all applicants in their insurance plan and ask a community-rated premium for the mandatory health insurance (Van de Ven & Ellis, 2000). However, the chance of using healthcare is not that equally distributed among the enrolees. The young and healthy have predictably lower healthcare costs than old and sick enrolees, because their risk of using healthcare is lower. The variation in predictable healthcare costs between low- and high-risk enrolees leads to predictable profits and losses for the insurer. A risk-equalization model compensates the insurers for these predictable profits and losses. This system has a prospective payment arrangement which adjusts for the risk differences among the low- and high-risks (De Pietro et al., 2015; Van de Ven & Ellis, 2000). Prospective payment arrangements are preferred over retrospective payment arrangements because retrospective payment arrangements give the insurers no incentives for cost-conscious behaviour and thus reduces efficiency. The risk-equalization model uses individual information of enrolees for the calculation of the expected healthcare costs over a fixed time period. (Schokkaert & Van de Voorde, 2006; Van de Ven & Ellis, 2000).

2.2. Risk selection

In practice, risk-equalization models are not perfect (Layton et al., 2018; Van Kleef et al., 2013). Even after sophisticated risk equalization, insurers are making predictable losses on the high-risk enrolees. A consequence of these imperfect risk-equalization models is that insurers might have incentives for risk selection. Although an open enrolment and a community-rated premium prevents insurers from simply refusing the high-risks or asking an extremely high premium, insurers can use more subtle forms of selection (Van Kleef et al., 2015; Van de Ven et al., 2003;). One of the subtle forms of risk selection is by structuring the health plan such that it is attractive for the predictably low-risks and unattractive for the high-risks (Van de Ven & Ellis, 2000). Insurers are structuring their health plan by having disincentives to contract the providers with a good reputation for the treatment and management of chronic diseases (Van de Ven & Ellis, 2000; Van de Ven, 2011). As a result, the quality of healthcare will be lowered, because when insurers do not want to contract the best providers, these providers will not acquire such a reputation anymore (Beck et al., 2020; Van Kleef et al., 2013; Van de Ven & Ellis, 2000; Van de Ven, 2011). Another unfavourable effect of risk selection is inefficiency. Because of the large predictable profits of risk selection, it might be more profitable for insurers to engage in risk selection than to improve the efficiency of the production of healthcare (Van Kleef et al., 2013; Van de Ven et al., 2003).

Theoretically, the best strategy to reduce risk selection is good risk equalization (Schokkaert & Van de Voorde, 2006; Van de Ven et al., 2003). Due to selection effects, a trade-off has to be made between efficiency and fairness objectives. The better the risk-equalization model is adjusted for risk, the more eliminated this trade-off will be (Van de Ven & Ellis, 2000; Van de Ven, 2011). Thus, improving the risk-equalization model will reduce the incentives for risk-selection. The aim of an adequate risk-equalization model formula is not to equalize the maximum potential variation in predicted healthcare

costs, but to compensate the insurer to prevent selection based on the risks of their enrolees (van Vliet, 1992).

2.2.1. Appropriateness of risk adjusters

Risk-equalization models compensate insurers for specific indicators. Not all possible indicators can be used in the system. It is crucial to use appropriate indicators with information that can be used to determine the risks of an enrolee. An indicator must meet several criteria which can be grouped in three main criteria. The appropriateness of incentives, fairness and feasibility (Van de Ven & Ellis, 2000).

Appropriateness of incentives

The aim of the risk-equalization model is to reduce the incentives for risk selection. Therefore, the appropriateness of incentives is an important criterium during the evaluation of the risk-equalization model. Incentives for risk selection can be reduced when risk-equalization models compensate insurers adequately. For that reason, a risk adjuster must have predictable power for future healthcare costs. Besides the incentives for reducing risk selection, it is also important to pay attention to the incentives for efficiency. Ideally, a risk adjuster does not contribute to a decrease in incentives for efficiency (Van Kleef et al., 2015; Van de Ven & Ellis, 2000). It is possible that a risk adjuster can be influenced by the insurer. This means that the health insurer has impact on the equalization contribution which can result in undesirable effects. Healthcare costs in the previous year is an example of a risk adjuster that can be influenced by the insurer. This adjuster creates a link between healthcare costs and the equalization contribution with undesirable disincentives for efficiency as result. Higher healthcare costs made this year results in a higher equalization contribution next year (Lamers & van Vliet, 1996; Lamers., 1997;Van de Ven & Ellis, 2000)

Fairness

The second criterium is the fairness of risk adjusters. Individual risk factors can be divided in S-type and N-type factors. S-type factors are the factors for which solidarity is desired, and N-type factors for which solidarity is not desired. Factors that reflect the taste of enrolees might be predictable, but are generally marked as N-type factors. For fairness principles it is important that the risk-equalization model only consists of the factors for which solidarity is desired. Nevertheless, it is difficult to make a strict division between S-type and N-type factors. For that reason, the characteristics of risk-equalization models differ between countries (Schokkaert & Van de Voorde, 2006; Van de Ven & Ellis, 2000). Perfect compensations for enrolees with chronic conditions will increase their access to healthcare because insurers will no longer have incentives to select against enrolees with high healthcare costs (Van de Ven & Ellis, 2000).

Feasibility

The choice of risk-adjusters is limited, due to feasibility problems. The risk adjuster should be measurable for the whole population without unnecessary investments of time or money (Van Kleef et al., 2015; Van de Ven & Ellis, 2000). Preferably the risk adjuster must be regularly collected, valid and must consist predictive power for future healthcare costs. However, the risk-equalization model cannot ignore the right to privacy of enrolees and providers (Van de Ven & Ellis, 2000). Self-reported

health status is an example of a variable with a predictive power for future healthcare costs. However, it is expensive and difficult to collect this information for the entire population (Fan et al., 2006).

2.3. The contribution of end-of-life spending to selection incentives for insurers

Polder et al. (2006) have found that healthcare costs are high for individuals in their last year of life. In 1999 the healthcare costs where on average 13.5 times higher for individuals who deceased than for those who did not decease in that year. Of the total healthcare expenses, 11.1% could be assigned to individuals in their last year of life (Polder et al., 2006). Stooker et al. (2001) found that, compared to other specific expenses, healthcare expenses are around 10% in the last year of life, which is a quite similar percentage to Polder et al. Thus, at the end of life there is a sharp rise of healthcare costs, especially in the last months of life (Polder et al., 2006; Stooker et al., 2001). Most costs in the final stage of life are made in hospital. The high healthcare costs in the final stage of life depend on several factors. Examples of those factors are age, national health expenditure and causes of death. There is a high variance in healthcare costs among the different causes of death. The highest costs were caused by diseases of the urinary tract, infectious diseases and musculoskeletal diseases. The costs among the most common causes of death were the highest for cancer (Polder et al., 2006).

Einav et al. (2018) have shown that it is possible to predict the probability of dying to a certain extent. Through machine learning techniques, predictions of the individual probability of dying in the next years are generated (Einav et al., 2018). Also, An et al. (2020) used machine learning to develop a prediction model for the probability of dying. They used this model to predict the probability of dying during the COVID-19 pandemic (An et al., 2020).

In sum, these prior studies point toward 1) high spending in the last year of life and 2) predictability of dying. In combination, these two findings suggest that enrolees with a high probability of dying have relatively high spending. To determine whether these enrolees are actually unprofitable to insurers, the effect of risk equalization needs to be taken into account. If enrolees with a higher risk of dying turn out to be unprofitable for insurers, insurers might get incentives to avoid these enrolees. A crucial question is to what extent the current risk-equalization model is compensating insurers for enrolees with a high probability of dying. This has not been studied before, but will be examined in this thesis.

It is essential that insures are adequately compensated for these predictable high healthcare costs to avoid incentives for risk selection. If it appears that insurers are not adequately compensated for enrolees with a high risk of dying, they might have incentives for risk selection. These incentives for risk selection can take place on two different levels, the individual and the subgroup level. Selection on the individual level can take place by prohibiting the access to supplementary insurance. Individuals prefer to have their basic and supplementary insurance at the same insurer. If an insurer wants to avoid that specific consumer the applicant can simply be refused for supplementary insurance. As a result, the applicant will choose another insurance company. Another example for selection on the individual level is by not investing in the best quality of healthcare and by offering low benefits (Van de Ven & Ellis, 2000). Insurers can also try to avoid the group of individuals with a high probability of dying, the subgroup level. On the subgroup level risk selection can take place by not contracting the

best quality healthcare for the groups of enrolees with a higher chance of dying. For example on palliative care, for specific cancer treatments or other treatments for groups with a higher probability of dying. However, when it is attractive to include an enrolee with a high probability of dying in the insurance plan, insurers might want to invest in buying better healthcare services that are related to the final stage of life.

2.4. Metrics for selection incentives

The third question of this research discusses the improvement of the risk-equalization model. In this research it will be measured if enrolees with a high probability of dying are predictably unprofitable for insurers. If so, the question is whether it is possible to reduce the (potential) predictable losses for these enrolees by including the risk adjuster "yes/no high probability of dying" in the current risk-equalization model. To evaluate the extent to which the selection incentives can be reduced by including this risk adjuster, several metrics will be used. As is discussed in the previous paragraph, risk selection can take place on the individual and on the subgroup level. The metrics for selection incentives that are going to be used in this research will also be divided in those two groups. In the literature the following metrics are used for the evaluation of risk-equalization models: R-squared (R^2), Cummings Prediction Measure (CPM) and mean financial result (Beck et al., 2020; Cumming et al., 2002; Layton et al., 2018; Van de Ven & Ellis, 2000).

One of the most used metrics in the evaluation of risk-equalization models is the R^2. This metric measures the difference between the predicted expenditures and the real expenditures on the individual level. The R^2 gives a higher weight to the measured variance in expenditures because it will be squared (Layton et al., 2018; Van de Ven & Ellis, 2000). Usually, a higher R^2 results in a better risk-equalization model (Beck et al., 2020; Layton et al., 2018). Another metric that can be used for the evaluation on the individual level is the CPM. This metric is quite similar to the R^2. However, the difference between the R^2 and CPM is that the measured difference will be linear when using CPM and squared when using an R^2 (Cumming et al., 2002; Van de Ven & Ellis, 2000; Layton et al., 2018). There might be a chance that the incentives for risk selection increase when the predictable profits and predictable losses are higher. The pay-off is higher when an insurer puts more effort in high predictable losses and profits, than the small predictable profits and losses. However, this does not have to be the case. It is unsure which metric is the right one (Van de Ven & Ellis, 2000). For that reason, both metrics will be used in this research to determine the variance in expenditures on the individual level.

In addition to the individual level, it is also important to take the subgroup level into account (Beck et al., 2020; Layton et al., 2018). The most likely way in which risk selection might take place is against or for specific subgroups. To measure selection incentives on the subgroup level the mean financial result will be used as a metric. The mean actual healthcare expenditures for a specific subgroup will be compared to the mean predicted healthcare expenditures from the risk-equalization model (Beck et al., 2020; Layton et al., 2018).

3. Research methods

This research used a quantitative study design. Answers to the research questions were obtained via a simulation analysis in the context of the Swiss basic health insurance. The Swiss basic health insurance is characterised by regulated competition and consists of regulated premiums which are community-rated per insurance plan per region. Insurers are compensated for predictable profits and losses via the risk-equalization model (Beck et al., 2020).

3.1. The Swiss risk-equalization model

In this paragraph the different risk adjusters that are used in the Swiss risk-equalization model are explained. In the Netherlands, the risk-equalization model is relatively sophisticated, whereas in Switzerland the system is more basic (Leu et al., 2009). Switzerland includes the following risk adjusters: age * gender, hospitalization in year t – 1 and PCGs based on the use of pharmaceuticals in year t – 1 (Beck et al., 2020).

One of the risk adjusters is the interaction between age and gender. In Switzerland this adjuster contains 28 classes, 14 age classes for men and 14 age classes for women. The age classes are: 0-18, 19-25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, 61-65, 66-70, 71-75, 75-80, 81+. These classes are all dummy variables, that means that the outcome of these variables is binary.

Another adjuster in the Swiss risk-equalization model is hospitalization in year t – 1. This adjuster is also a dummy variable and turns one if an enrolee has spent more than three consecutive days in the hospital or nursing home in the prior year (De Pietro et al., 2015).

Pharmacy-based Costs Groups (PCGs) are based on the use of pharmaceuticals in year t – 1 and can be used for the measurement of morbidities (Lamers & van Vliet, 2004). The PCGs are also all dummy variables. Enrolees with a specific chronic disease can be assigned to one or more of those groups. For example, enrolees who use insulin in the prior year can be assigned to the PCG for diabetes. In Switzerland PCGs are divided in 28 different conditions. (De Pietro et al., 2015)

3.2. Data sources

During the study the dataset of a Swiss health insurer was used. This is an administrative dataset under the Swiss basic health insurance which consists of individual-level spending and risk characteristics for about 1.3 million enrolees. The dataset is accessible for four consecutive years, 2013 – 2016. 2016 is denoted as year t. The years t – 1, t – 2 and t – 3 are respectively the years 2015, 2014 and 2013. Before the data-analysis could be performed, the data needed some preparation. The several datasets that were used were merged into one dataset. Dummy variables were created for all categorical variables. All duplicate records (i.e. insured that occurred in the data multiple times) were removed. For the duplicates that existed because an enrolee moved to another canton, the total healthcare costs in the different cantons were summed. Only enrolees that appeared in the whole four-year period datasets were included in this research. The reason for this inclusion criterium is that administrative information for the four consecutive years were used in the prediction model. Enrolees born in year t, t – 1 or t – 2 and enrolees deceased in year t – 1, t – 2 or t – 3 were excluded from the

dataset. As a result, the dataset of 1.3 million enrolees declined to 994,333 enrolees. Because of the access to this specific dataset it was not found necessary to collect other data in this study. For all three research questions, regression analysis was used and the simulation analysis was performed by using the program R version 4.0.4.

3.3. Data analysis

The three research questions were answered in chronological order and were divided in three parts. A validation set approach was used to randomly split the dataset in two sets, the train and the test set (Kassambara, 2018). The train set, which contains a random sample of 10,000 enrolees, is only used to develop the prediction model in part 1. For the individual estimation of the probability of dying and the simulation of both the current and the new risk-equalization model in part 2 and 3, the test dataset of 984,333 enrolees is used.

3.3.1. Part 1 – The predictability of dying

First, the predictability of dying was researched using a stepwise logistic regression. Options for using machine learning techniques instead of a stepwise logistic regression were explored during the research. The large dataset, the limited time frame and the limited ability of the computer used made it impossible to use machine learning during the research. Therefore, a stepwise logistic regression was used. The stepwise logistic regression was performed on the train set, which consist of 10,000 enrolees of the dataset. It was impossible to take a larger sample for this selection, again this was due to the limited ability of the computer. An explanatory model was developed with a dummy outcome variable: dying in year t. The probability of dying in year t is explained by the relation between enrolees who actually deceased in year t and information from previous years available at the start of year t. These independent variables are: age * gender, total healthcare costs (CHF) in each of the years t – 1, t – 2 and t – 3, hospitalization in each of the years t – 1, t – 2 and t – 3 and pharmacy-based cost groups based on use of pharmaceuticals in each of the years t – 1, t – 2 and t – 3. Dummy variables were created for all variables which resulted into one outcome variable and 122 possible explanatory variables. The stepwise logistic regression selected variables by iteratively adding and removing them in order to acquire the best performing explanatory model with a reduced set of variables (Kassambara, 2018). The developed explanatory model with selected variables was used as a prediction model. The ex-ante probability of dying in year t was estimated for every individual in the test dataset. This test dataset contains all enrolees in the whole dataset except the 10,000 enrolees which were used for the development of the model. Based on the individual probability of dying, enrolees were divided into two groups, enrolees with a low probability of dying and enrolees with a relatively high probability of dying. A new dummy variable was created with value = 1 for enrolees assigned to the group with a high probability of dying and value = 0 for enrolees assigned to the group with a low probability of dying.

3.3.2. Part 2 – Risk equalization for enrolees with a relatively high probability of dying

Based on the predicted probability of dying in year t for enrolees in the test dataset, a specific group of enrolees with a relatively high probability of dying was identified in part 1. In part 2, it was examined to what extent the current risk-equalization model compensates insurers for this specific group. The

current Swiss risk-equalization model was simulated by using an ordinary least squares (OLS) regression analysis with healthcare costs in year t as the outcome variable. The independent variables were equal to the characteristics of the Swiss risk-equalization model. These are already discussed in paragraph 3.1 and are: age * gender, hospitalization in year t – 1 and PCGs which are derived from the use of pharmaceuticals in year t – 1. The simulation model was used to predict the healthcare costs in year t for every individual. The predicted healthcare costs were the actual equalization contribution the insurer receives for that individual. The predicted healthcare costs in year t are compared to the actual healthcare costs in year t. The calculated difference in outcome is the estimated financial result for that individual. Subsequently, the mean financial result was determined for the specific group of insured persons with a relatively high probability of dying in year t. Besides the mean financial result, the metrics R^2 and the CPM are also determined for the current risk-equalization model.

3.3.3. Part 3 – Expansion of the risk-equalization model

A new risk adjuster was added to the simulation of the risk-equalization model in the last part. This risk adjuster expands the current Swiss risk-equalization model with the dummy variable "yes/no high probability of dying". The new risk-equalization model was simulated by repeating part 2 of this research with this new risk adjuster. Thereafter, the simulation of the current risk-equalization model was compared with the simulation of the new risk-equalization model. This comparison allowed determining whether the new risk-equalization model is better than the current risk-equalization model in preventing incentives for risk selection. First, the R^2 and the CPM were examined for the new risk-equalization model and compared to those of the current risk-equalization model. Furthermore, the mean financial result for the specific group, the enrolees with a relatively high probability of dying, is determined. Given the properties of OLS regression (the estimation method for the risk-equalization models) it may be expected that the inclusion of the new risk adjuster in the new risk-equalization model will eliminate the under-/overcompensation of this specific group (Wheelan, 2013). After the calculation of the mean financial result for the subgroup with a high probability of dying, insight was gained in other subgroups. Based on the probability of dying, the enrolees were divided over 10 deciles and the mean financial result for the current and new risk-equalization model was calculated. Additionally, the same division took place by dividing enrolees over 10 deciles based on their healthcare costs in year t – 1. Besides showing the 10 deciles, also the highest 10 percentiles were presented for these subgroups.

3.4. Evaluation Metrics

The metrics that were chosen for the evaluation of the risk-equalization models in part 2 and 3 of the research can be further explained. As written in the theoretical framework, the metrics can be divided in the individual and the subgroup level.

The first metric that was used is the R^2. This metric is explained in equation 1. In this equation Y_i can be defined as the actual expenditure of individual i. $\bar{Y}$ is the average expenditure of the population in the dataset. $\hat{Y}_i$ is in this equation the predicted expenditure of individual i. The denominator in this equation, $\sum_i (Y_i - \bar{Y}_i)^2$, can be explained as the total sum of squares of individual expenditures. The higher this value, the more widespread the expenditures around the mean $\bar{Y}$ are. The numerator,

$\sum_i (Y_i - \hat{Y}_i)^2$, measures the sum of squared errors. The closer the predicted expenditures are to the actual expenditures, the smaller the sum of squared errors. The range of risk-equalization models is normally between $0 \leq R^2 \leq 1$. The better the predicted expenditures fit in the actual expenditures, the closer the R^2 will be to one. It is also possible to determine the R^2 as the percentage of the total variance explained by the risk-equalization model (Layton et al., 2018).

$$R^2 = 1 - \frac{\sum_i (Y_i - \hat{Y}_i)^2}{\sum_i (Y_i - \bar{Y}_i)^2} \qquad \text{(Equation 1)}$$

The second metric that was used for the evaluation of the risk-equalization models on the individual level is the CPM. This metric is visible in equation 2. As discussed before, CPM is quite similar to the R^2 metric. The difference between these two metrics is that CPM looks at absolute errors instead of squared errors. For this reason, CPM is not overly sensitive to large values. If equation 1 and 2 are compared, this difference is visible (Cumming et al., 2002). Because the formula is quite similar to the R^2, this will not be further explained.

$$CPM = 1 - \frac{\sum_i |Y_i - \hat{Y}_i|}{\sum_i |Y_i - \bar{Y}_i|} \qquad \text{(Equation 2)}$$

Selection actions on the individual level can take place by prohibiting supplementary insurance of those enrolees and/or lacking the provision of good quality healthcare services (Van de Ven & Ellis, 2000). It is also possible that health plans discriminate on the subgroup level. For example, by not purchasing the best healthcare for specific diseases. In addition to the metrics used for the individual level, a metric was used to evaluate plan discrimination on the subgroup level, called the over-/undercompensation or mean financial result. This metric is defined in equation 3. A part of this equation is equal to equation 1. $\hat{Y}_i$ is the predicted expenditure of individual i valued from the risk equalization regression and Y_i is the actual expenditure of individual i. $i \in g$ stands for the individuals in the group, g. n_g indicates the number of individuals in group g. The average mean financial result for group g is the measured over-/undercompensation. This mean financial result is in monetary terms, which is Swiss franc (CHF) in this case. When the outcome of this metric is close to zero for group g, then there are no incentives to select against (in case of undercompensation) or in favour (in case of overcompensation) of group g. The higher the mean financial result, the larger the incentives for discrimination in favour or against the subgroup are (Layton et al., 2018).

$$Over-/Undercompensation_g = \frac{\sum_{i \in g} (\hat{Y}_i - Y_i)}{n_g} \qquad \text{(Equation 3)}$$

4. Results

4.1. Descriptive statistics

The healthcare expenditures for four consecutive years are presented in Table 1. The mean total healthcare costs per individual for year t, t – 1, t – 2 and t – 3 are respectively 4290, 3920, 3540 and 3220 CHF. Remarkable is that the total healthcare costs rise every year. This might be an effect of the inclusion criterium which is discussed in the method section. Only enrolees that appear in the whole four year period are included in the dataset. The healthcare costs of enrolees that were born in year t, t – 1, or t – 2 or deceased in year t – 1, t – 2, or t – 3 are not included in the calculated mean total healthcare costs. This means, for example, that in year t – 3 the healthcare costs for enrolees who deceased in that year or in one of the two years thereafter are not included in the calculated mean healthcare costs for year t – 3. The healthcare costs for year t – 1, t – 2 and t – 3 could be higher if the healthcare costs for enrolees who deceased in these years were taken into account. Despite excluding the enrolees who deceased in year t – 1, t – 2 and t – 3, enrolees who deceased in year t are included in the calculated mean healthcare costs. The raise in healthcare costs over the four years is an effect that might occur because enrolees who deceased were only included in the calculation of the average healthcare costs of year t. Those enrolees have on average high healthcare costs (Polder et al., 2006; Stooker et al., 2001).

Table 1 – Mean total healthcare costs (CHF) in year t, t – 1, t – 2 and t – 3 with the use of a Swiss dataset (N = 994,333)

	Mean	SD	Median [Min., Max.]
Healthcare costs in year t (CHF)[a]	4290	10600	1080 [0, 1410000]
Healthcare costs in year t – 1 (CHF)[a]	3920	9790	990 [-33.8, 1040000]
Healthcare costs in year t – 2 (CHF)[a]	3540	9010	920 [-29.4, 1060000]
Healthcare costs in year t – 3 (CHF)[a]	3320	8330	830 [-164, 1410000]

[a] Year t is the prediction year 2016. Years t – 1, t – 2 and t – 3 are respectively the years 2015, 2014 and 2013

Table 2 shows a summary of the variables in the dataset. The complete version of the used dataset is displayed in Appendix A. On the left side of Table 2 the frequencies of the enrolee characteristics are presented. Additionally, on the right side of Table 2 the mean total healthcare costs in year t are shown for the specific groups. It can be observed that 1.0% of the total enrolees (994,333) deceased in year t. The mean healthcare costs for the group that decease is 22735 CHF, which is 18623 CHF higher than the 4112 CHF for the group that does not decease in year t. This means that there is a relation between the last year of life and high healthcare costs. Nevertheless, this interesting result is not an answer for this research, because it cannot be determined beforehand who will decease and who will not. In this research will not be looked at the mean healthcare costs for enrolees that actually decease, but the mean financial result for enrolees with a high probability of dying will be investigated.

Besides the enrolees who decease and who not decease, other enrolee characteristics are presented in Table 2. The 28 classes for the interaction between age and gender are summarized in four classes, two for women and two for men. 35.9% of the population were women and 60 or younger years old. 16.0% were women and older than 61. When summing up these percentages it can be concluded that 51.9% of the population were women and thus 48.1% men. 35.5% of those men are younger than 61

and 12.6% are 61 or older. The mean healthcare costs in year t are higher for enrolees with the age of 61 or older which is 8804 CHF for women and 8579 CHF for men. For enrolees with the age of 60 or below the average healthcare costs are 2921 CHF for women and 2125 CHF for men. It can be concluded from these numbers that the healthcare costs are on average higher for women than for men. Of all enrolees, 7.3% has laid in the hospital for 3 consecutive nights in year t – 1. In year t – 2 this is 6.7% and in t – 3 this is 6.3%. The mean healthcare costs in year t – 1 for these groups are 17092, 15313 and 14321 CHF, respectively. Table 2 summarized all PCGs together and only shows whether an enrolee was assigned to one or more PCGs. 25.8% of the enrolees are assigned to one or more PCGs in year t – 1. In year t – 2 this was 24.8% and in year t – 3 23.8%. The corresponding mean healthcare costs are 10401, 10192 and 10179. The percentages of enrolees assigned to the specific 28 PCGs are visible in appendix A. Besides presenting the total dataset, this appendix also shows the characteristics for enrolees in the train dataset which is used in part 1. As noticed in the first paragraph of this chapter, the inclusion criterium of only selecting enrolees that appeared in the four year dataset has some side effects. In Table 2, those side effects are visible in the variables hospitalization in year t – 1, t – 2 and t – 3 and PCGs based on use of pharmaceuticals in those years. It can be seen that for both the variables, the frequency and the mean total healthcare costs are higher in year t – 1 and decline in year t – 2 and t – 3. This does not per se mean that more enrolees were assigned to PCGs or have laid in the hospital in year t – 1, because the enrolees who deceased in year t – 1, t – 2 and t – 3 were not included in the dataset.

Table 2 – Frequencies of enrolee characteristics and mean healthcare costs in year t

	Frequency (%) Total (N=994,333)	**Mean total healthcare costs in year t** (CHF)[a]
Deceased in year t[a]		
Deceased	1.0%	22735
Alive	99.0%	4112
Age * Gender[b]		
Women age 60-	35.9%	2921
Men age 60-	35.5%	2125
Women age 61+	16.0%	8804
Men age 61+	12.6%	8579
Hospitalization in [c]		
Year t – 1[a]	7.3%	17092
Year t – 2[a]	6.7%	15313
Year t – 3[a]	6.3%	14321
PCGs based on use of pharmaceuticals in		
Year t – 1[a]	25.8%	10401
Year t – 2[a]	24.8%	10192
Year t – 3[a]	23.8%	10179

[a] Year t is the prediction year 2016. Years t – 1, t – 2 and t – 3 are respectively the years 2015, 2014 and 2013
[b] Age * Gender is the interaction between age and gender
[c] Hospitalized for three or more consecutive nights

4.2. Part 1 – The predictability of dying

A prediction model is developed using a stepwise logistic regression analysis on the train set of 10,000 enrollees with “deceased in year t” as outcome variable. The model selected 42 variables out of 122 explanatory variables for the prediction of the probability of dying. The correlations of these

independent variables with the dependent variable, “deceased in year t”, are visible in Table 3. The size of the coefficient is related to the size of the effect the variable has on the outcome variable. As can be seen in Table 3, the coefficient for hospitalization in year t – 1 is large and positive. This means that this variable has a large contribution to the probability of dying. Besides hospitalization in year t – 1, several higher age groups also have a large impact on the probability of dying. Especially the highest age groups of 81 years and older. The coefficients for the different years of PCGs are widespread. Most of them are large and have a positive or negative impact on the probability of dying. This effect can be a result of the variable healthcare costs in year t – 1. The coefficient of this variable is 0.0004. This small coefficient does not seem to stand out. However, it needs to be taken into account that the variable healthcare costs in year t – 1 is the only continuous variable and for that reason this is the most important variable in the prediction model. This means, for example, that if an individual has 1000 CHF healthcare costs, the coefficient of this variable is already 4.0. Thus, the higher the individual healthcare costs, the higher the coefficient of this variable is. This can explain the large variance between the different PCGs. Not all selected variables are significant. Especially the different age groups do not indicate a p-value below 0.05 and thus are insignificant. However, the stepwise regression analysis selected these variables and for that reason they are included in the prediction model.

Metrics for the prediction model are presented at the bottom of Table 3. The first metric is the Pearson chi-square (X^2) which determines if the prediction model performs well in making predictions by comparing the model to the actual observed data. The X^2 in this model is 436.25 and the p-value is 0.000. With a p-value of 0.000 it can be concluded that there is a significant relationship between the independent variables and the dependent variable, “deceased in year t”. Another metric that is measured is the pseudo-R^2. A pseudo-R^2 of 0.41 means that this model is quite good at predicting the probability of dying. The metrics are calculated on the train set and show the extent to which the prediction model is good at predicting for the train set. Hence, there might be some degree of overfitting. However, the exact degree of overfitting is unknown. It is important for the following steps to continue with the test set to rule out any bias due to overfitting.

Table 3 – Logistic regression with yes/no deceased in year t as dependent variable and a series of individual characteristics as independent variables

	Dependent variable: Deceased in year t		
	Coefficient	**SE**	**P-value**
(Intercept)	-6.886	0.345	0.000***
Hospitalization in[c]			
Year t – 1[a]	1.083	0.330	0.001***
Year t – 2[a]	0.615	0.285	0.031*
Age * Gender[b]			
Women age 26-30	-0.386	1.654	0.826
Women age 51-55	0.316	1.059	0.765
Men age 51-55	0.723	0.812	0.373
Women age 56-60	0.719	0.830	0.386
Men age 56-60	1.197	0.704	0.089.
Women age 61-65	0.596	1.061	0.574
Men age 61-65	-0.077	1.114	0.945
Women age 66-70	0.588	0.831	0.479

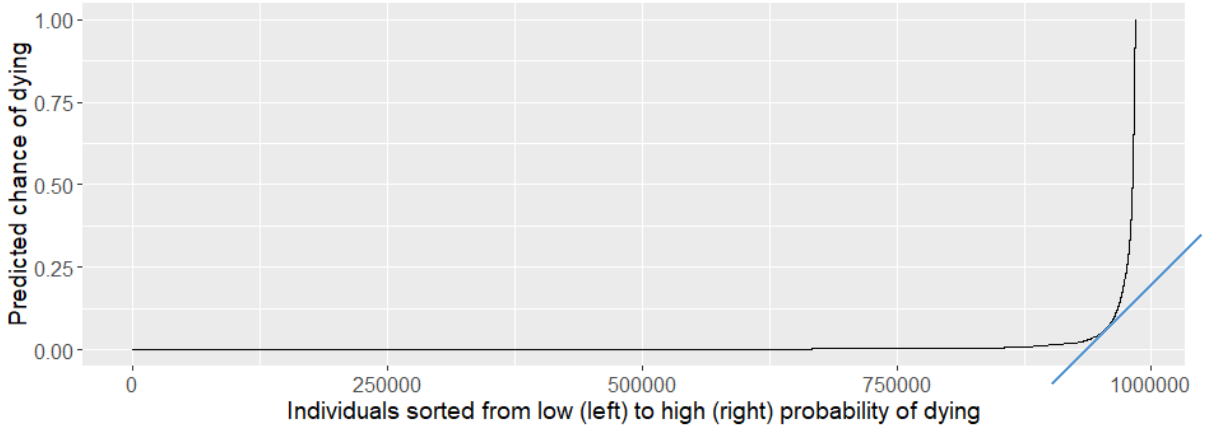
	Dependent variable: Deceased in year t		
	Coefficient	**SE**	**P-value**
Men age 66-70	1.446	0.657	0.028*
Women age 76-80	1.476	0.656	0.025*
Men age 76-80	1.892	0.591	0.001***
Women age 81+	2.817	0.427	0.000***
Men age 81+	2.773	0.452	0.000***
PCGs based on use of pharmaceuticals in year t – 1[a]			
PCG16num1	0.988	0.512	0.054
PCG16num4	0.974	0.377	0.010**
PCG16num6	-0.336	0.293	0.251
PCG16num8	-2.782	1.725	0.107
PCG16num10	1.523	0.579	0.009**
PCG16num13	-3.868	1.838	0.035*
PCG16num15	-0.592	0.478	0.215
PCG16num16	-2.694	0.889	0.002**
PCG16num17	-1.412	1.052	0.179
PCG16num26	-19.664	591.412	0.973
PCGs based on use of pharmaceuticals in year t – 2[a]			
PCG15num13	7.400	2.459	0.003**
PCG15num16	2.663	0.772	0.001***
PCG15num17	1.606	1.291	0.213
PCG15num23	-3.036	1.505	0.044*
PCG15num25	-16.759	1603.248	0.992
PCGs based on use of pharmaceuticals in year t – 3[a]			
PCG14num2	-3.091	1.922	0.108
PCG14num3	-2.330	1.147	0.042*
PCG14num5	1.904	0.863	0.027*
PCG14num8	2.527	1.726	0.143
PCG14num10	-1.551	1.126	0.168
PCG14num11	1.755	0.618	0.005**
PCG14num13	-4.118	2.077	0.047*
PCG14num15	1.355	0.429	0.002**
PCG14num17	-1.488	1.081	0.169
PCG14num23	3.382	1.314	0.010**
PCG14num28	-15.653	835.305	0.985
Healthcare costs in year t – 1[a]	0.00004	0.000	0.000***
$\chi^2(42) = 436.25$, p = 0.00			
Pseudo-$R^2 = 0.41$			

[a] Year t is the prediction year 2016. Years t – 1, t – 2 and t – 3 are respectively the years 2015, 2014 and 2013
[b] Age * Gender is the interaction between age and gender
[c] Hospitalized for three or more consecutive nights
* p ≤ 0.05. ** p ≤ 0.01. *** P ≤ 0.001

The prediction model is used to estimate the chance of dying for every enrolee in the test dataset. The train dataset of 10,000 enrolees, which is used to develop the prediction model, is excluded from this test dataset. Figure 1 is used to divide enrolees between two groups based on their probability of dying. The predicted chance of dying for all enrolees in the test dataset is visible in Figure 1. The lowest predicted chances are displayed on the left side of Figure 1, whereas the highest predicted chances are displayed at the right side of Figure 1. For most enrolees the predicted chance of dying is close to zero. At the far left of Figure 1 a steep ascending line is visible. A 45-degree line is used to estimate an arbitrary turning point from which enrolees have a relatively high probability of dying. The tangent of the graph to this 45-degree line is the turning point, which is at a predicted chance of dying of 0.05 percent. Enrolees with a predicted chance of dying that is equal or higher than the turning point are

assigned to the group “yes/no high probability of dying”. In absolute terms, a predicted chance of dying of 0.05 percent is still low. However, in relative terms, the predicted chance of dying is higher compared to enrolees with a low predicted chance of dying.

Figure 1 – Predicted chance of dying for all individuals in the test dataset (N = 984333) which are sorted from low (left) to high (right) probability of dying.



The characteristics of both groups, low and high probability of dying, are presented in Table 4. As can be seen in Table 4, the group of enrolees with a high predicted probability of dying contains 3.4% of the enrolees whereas the group with a low predicted chance of dying is represented by 96.6% of the enrolees. When focussing on the group with a high probability of dying it can be seen that 14.5% of this group is actually dying in year t, whereas 85.5% stays alive. For the group with a low probability of dying 0.5% is actually dying and 99.5% does not die. Enrolees assigned to the group of a high probability of dying are more often women and aged 61 or above (55.2%). Also, men aged 61 or above are highly represented in the group with a high probability of dying with 37.2%. 75.2% of the group with a high probability of dying was hospitalized three or more consecutive nights in year t – 1. In year t – 2 and t – 3 this was lower with 51.1% and 38.3%, respectively. In this group the percentages for the enrolees assigned to one or more PCGs in prior years are quite high and stable for all three years with 74.1%, 74.8% and 74.3% in year t – 1, t – 2 and t – 3. The mean prior healthcare costs are in all three years higher for the group with a high probability of dying than for the group with a low probability of dying. For the high probability of dying group these costs are in year t – 1, year t – 2 and in year t – 3 respectively 29700, 20100 and 15600 CHF. For the group with a low probability of dying these are 3020, 2960 and 2790 CHF, respectively.

From these frequencies of groups can be concluded that the prediction model is performing well. The group with a high probability of dying (left side of Table 4) has a chance of dying which is 30 times as big as the group with a low probability of dying (right side of Table 4). As might be expected, based on the coefficients of the prediction model, the group with a relatively high chance of dying is on average older, has been hospitalized more often in the previous years, has been assigned more often to PCGs in prior years and has on average higher costs in previous years. This is a logical pattern, because due to the inherency to the prediction model, this is partly the reason that those enrolees were assigned to this group.

Table 4 - Enrolee characteristics for both groups, high- and low probability of dying

	High probability of dying 3,4% (N = 33.075)	**Low probability of dying 96,6% (N = 951.258)**
Deceased in year t[a]		
Deceased	14.5%	0.5%
Alive	85.5%	99.5%
Age * Gender[b]		
Women age 60-	3.3%	37.1%
Men age 60-	4.3%	36.6%
Women age 61+	55.2%	14.7%
Men age 61+	37.2%	11.7%
Hospitalization in[c]		
Year t – 1[a]	75.2%	4.9%
Year t – 2[a]	51.1%	5.1%
Year t – 3[a]	38.3%	5.2%
PCGs based on use of pharmaceuticals in		
Year t – 1[a]	74.1%	24.1%
Year t – 2[a]	74.8%	23.0%
Year t – 3[a]	74.3%	22.0%
Prior Healthcare costs		
Year t – 1 (Mean (SD))[a]	29700 (32400)	3020 (6250)
Year t – 2 (Mean (SD))[a]	20100 (28300)	2960 (6820)
Year t – 3 (Mean (SD))[a]	15600 (25300)	2790 (6630)

[a] Year t is the prediction year 2016. Years t-1, t-2 and t-3 are respectively the years 2015, 2014 and 2013
[b] Age * Gender is the interaction between age and gender
[c] Hospitalized for three or more consecutive nights

4.3. Part 2 – Risk equalization for enrolees with a relatively high probability of dying

The current Swiss risk-equalization model is simulated on the test dataset. The left column of Table 6 shows the results of the current Swiss risk-equalization model. For practical reasons it has been decided to present these results in the same table as the new risk-equalization model that will be discussed later. The size of the coefficient can be related to the size of the effect that variable has on the dependent variable, predicted healthcare costs. The direction of the effect can be derived from whether the coefficient is positive or negative. On the left side of Table 6 it is visible that besides high coefficients for specific PCGs, the coefficient for hospitalization in year t – 1 is one of the highest. This means that if someone was hospitalized in year t – 1, the expected healthcare costs are higher this year. Another effect that can be seen from the left side of Table 6 is that the coefficients increase when the age increases. For men, the coefficient is negative till the age of 30. For women the coefficient is high between the age of 25 and 40, especially between the age of 31 and 35. This is an expected result, because most women give birth during this period in their life explaining the high expected healthcare costs. After the age of 40 this coefficient declines and starts increasing again. Till the age of 55 the coefficient is higher for women than for men. This means that the predicted healthcare costs are higher for women than for men till that age. However, after the age of 55 the coefficient is higher for men than for women. There are large differences in the size of the coefficients between the specific numbers of PCGs in year t – 1. Extremely high coefficients are visible for the numbers 9, 10, 12 and 13.

The corresponding metrics to the current risk-equalization model are shown in Table 5. Table 5 consists of three different metrics: R^2, CPM and mean financial result. These metrics evaluate the extent to which the model is compensating insurers for the healthcare costs. The R^2 is 0.258. This means that 25,8% of the total variance in healthcare spending in year t can be explained by the risk-equalization model. With a value of 0.265, the CPM is close to the value of the R^2. For this reason, it can be concluded that the current risk-equalization model is not overly sensitive to large values. The third metric that is used is the mean financial result for the group with a high probability of dying. The mean financial result for the current risk-equalization model is -6202 CHF. This is a negative value, which means that there is an average undercompensation for this group of 6202 CHF. Insurers are on average undercompensated by 6202 CHF for every enrolee in the group with a high probability of dying. This large undercompensation means that there are indeed incentives for risk selection. After all, insurers receive an average of CHF 6202 less per enrolee with an increased risk of dying. Thus, it might be attractive for insurers to avoid the individuals with a high probability of dying.

Table 5 – Metrics associated with the current risk-equalization model

Metric	**Current risk-equalization model (part 2)**
R^2	0.258
CPM	0.265
Mean financial result for the group with a high probability of dying (CHF)	- 6201.80

4.4. Part 3 – Expansion of the risk-equalization model

Besides presenting the current risk-equalization model on the left side of Table 6, the new risk-equalization model is presented on the right side of Table 6. This new risk-equalization model is an expansion of the current risk-equalization model. In this model the risk adjuster “yes/no high probability of dying” is added to the current risk-equalization model. The coefficient of this new variable is 11045.6, which means that the new risk-equalization model is largely influenced by this variable. The p-value of this risk adjuster is 0.000, that means that this risk adjuster is significant. A consequence of adding the new variable to the current risk-equalization model is that some shifts in coefficients take place. A large decrease is measurable for the variables hospitalization in year t – 1 and men and women aged 81 or higher. As mentioned in part 1 of the result section, the coefficients for these variables were also high in the prediction model. For that reason, these shifts can be explained by the fact that the new risk adjuster “yes/no high probability of dying” is mainly based on these variables. The influence of these variables on the new variable result in lower coefficients for these variables in the new risk-equalization model.

Table 6 – Current and new risk-equalization model

	Dependent variable: Healthcare costs in year t					
Model	**Current risk-equalization model (part 2)**			**New risk-equalization model (part 3)**		
Predictors	**Coefficient**	**SE**	**P-value**	**Coefficient**	**SE**	**P-value**
(intercept)	959.0	32.6	0.000***	995.4	32.2	0.000***
Hospitalization in year t – 1[a,c]	8140.0	38.0	0.000***	5361.0	40.9	0.000***
Age * Gender[B]						
Men age 0-18	-61.5	45.5	0.177	-59.1	44.9	0.188
Women age 19-25	545.5	56.1	0.000***	576.7	55.3	0.000***
Men age 19-25	-159.4	55.4	0.004**	-146.8	54.7	0.007**
Women age 26-30	1123.9	61.9	0.000***	1162.5	61.0	0.000***
Men age 26-30	-106.3	62.4	0.089	-93.7	61.6	0.128
Women age 31-35	1638.6	61.9	0.000***	1674.8	61.0	0.000***
Men age 31-35	36.7	62.0	0.554	50.6	61.2	0.408
Women age 36-40	1241.3	62.0	0.000***	1283.6	61.2	0.000***
Men age 36-40	73.0	63.4	0.249	87.5	62.5	0.161
Women age 41-45	933.1	59.8	0.000***	986.4	59.0	0.000***
Men age 41-45	318.8	61.7	0.000***	354.6	60.9	0.000***
Women age 46-50	971.8	55.9	0.000***	1043.6	55.1	0.000***
Men age 46-50	468.9	57.1	0.000***	518.5	56.3	0.000***
Women age 51-55	1157.6	55.3	0.000***	1223.4	54.6	0.000***
Men age 51-55	909.3	55.7	0.000***	940.2	54.9	0.000***
Women age 56-60	1223.8	57.6	0.000***	1249.2	56.8	0.000***
Men age 56-60	1384.6	58.1	0.000***	1356.7	57.3	0.000***
Women age 61-65	1446.1	60.5	0.000***	1498.6	59.6	0.000***
Men age 61-65	2038.2	61.4	0.000***	2195.1	60.5	0.000***
Women age 66-70	1948.4	61.4	0.000***	2028.0	60.6	0.000***
Men age 66-70	2694.2	63.8	0.000***	2516.4	63.0	0.000***
Women age 71-75	2633.9	63.9	0.000***	2827.3	63.0	0.000***
Men age 71-75	3746.7	67.9	0.000***	4006.2	66.9	0.000***
Women age 76-80	3331.3	69.7	0.000***	3014.2	68.8	0.000***
Men age 76-80	4395.4	77.7	0.000***	3617.2	76.7	0.000***
Women age 81+	5303.1	59.4	0.000***	2286.4	61.2	0.000***
Men age 81+	5337.6	72.1	0.000***	2368.1	73.3	0.000***
PCGs based on use of pharmaceuticals in year t – 1[a]						
PCG number 1	1691.3	61.8	0.000***	1172.1	61.1	0.000***
PCG number 2	5856.9	110.9	0.000***	6440.9	109.5	0.000***
PCG number 3	1985.2	62.2	0.000***	2563.5	61.4	0.000***
PCG number 4	3457.3	83.2	0.000***	1104.4	83.2	0.000***
PCG number 5	8728.5	157.9	0.000***	7613.3	155.8	0.000***
PCG number 6	4532.5	35.8	0.000***	4567.2	35.3	0.000***
PCG number 7	8030.6	136.6	0.000***	7656.8	134.8	0.000***
PCG number 8	7259.9	126.1	0.000***	7542.0	124.4	0.000***
PCG number 9	16218.8	286.9	0.000***	15107.8	283.0	0.000***
PCG number 10	15335.9	98.5	0.000***	13099.4	98.0	0.000***
PCG number 11	1068.6	111.3	0.000***	357.9	109.8	0.001***
PCG number 12	19570.7	212.1	0.000***	19236.8	209.2	0.000***
PCG number 13	33592.0	272.8	0.000***	32442.2	269.0	0.000***
PCG number 14	2493.1	58.1	0.000***	2648.7	57.3	0.000***
PCG number 15	186.8	54.4	0.000***	125.4	44.8	0.005**
PCG number 16	1333.3	64.8	0.000***	1620.7	63.9	0.000***
PCG number 17	973.1	53.2	0.000***	1570.1	52.6	0.000***
PCG number 18	1263.2	115.5	0.000***	1316.1	113.9	0.000***
PCG number 19	1400.2	121.0	0.000***	1431.0	119.3	0.000***

	Dependent variable: Healthcare costs in year t					
Model	**Current risk-equalization model (part 2)**			**New risk-equalization model (part 3)**		
Predictors	**Coefficient**	**SE**	**P-value**	**Coefficient**	**SE**	**P-value**
PCG number 22	3954.4	42.0	0.000***	3781.5	41.4	0.000***
PCG number 23	4449.2	129.6	0.000***	4394.4	127.8	0.000***
PCG number 24	3657.4	280.1	0.000***	3855.4	276.2	0.000***
PCG number 25	4389.3	202.7	0.000***	6668.3	200.3	0.000***
PCG number 26	5481.7	133.8	0.000***	6924.8	132.3	0.000***
PCG number 27	5158.4	102.1	0.000***	4929.4	100.7	0.000***
PCG number 28	2339.4	160.1	0.000***	2479.3	157.9	0.000***
Group with high probability of dying				11045.6	65.5	0.000***

[a] Year t is the prediction year 2016. Year t – 1 is year 2015
[B] Age * Gender is the interaction between age and gender
[C] Hospitalized for three or more consecutive nights
* p ≤ 0.05. ** p ≤ 0.01. *** P ≤ 0.001

In addition to Table 6, the corresponding metrics of the new risk-equalization model are presented in Table 7. For ease of comparison, the metrics of the current risk-equalization model, which are already presented in Table 5, are also included in Table 7. The R^2 has a value of 0.279 for the new risk-equalization model, which is slightly higher than the current risk-equalization model with a value of 0.258. This means that the new risk-equalization model is a bit better in compensating insurers for the healthcare costs than the current risk-equalization model. Also, the CPM is higher for the new risk-equalization model with a value of 0.274 for the new risk-equalization model and a value of 0.265 for the current risk-equalization model. The difference between the mean financial result for the group with a high probability of dying is larger. As mentioned before there is a mean undercompensation of -6202 CHF for the group with a high probability of dying for the insurers when using the current risk-equalization model. The new risk-equalization model eliminates this undercompensation for the insurers and has a mean financial result which is exact zero.

Table 7 – Metrics associated with the current and new risk-equalization model

Metric	**Current risk-equalization model (part 2)**	**New risk-equalization model (part 3)**
R^2	0.258	0.279
CPM	0.265	0.274
Mean financial result for the group with a high probability of dying (CHF)	- 6201.80	0

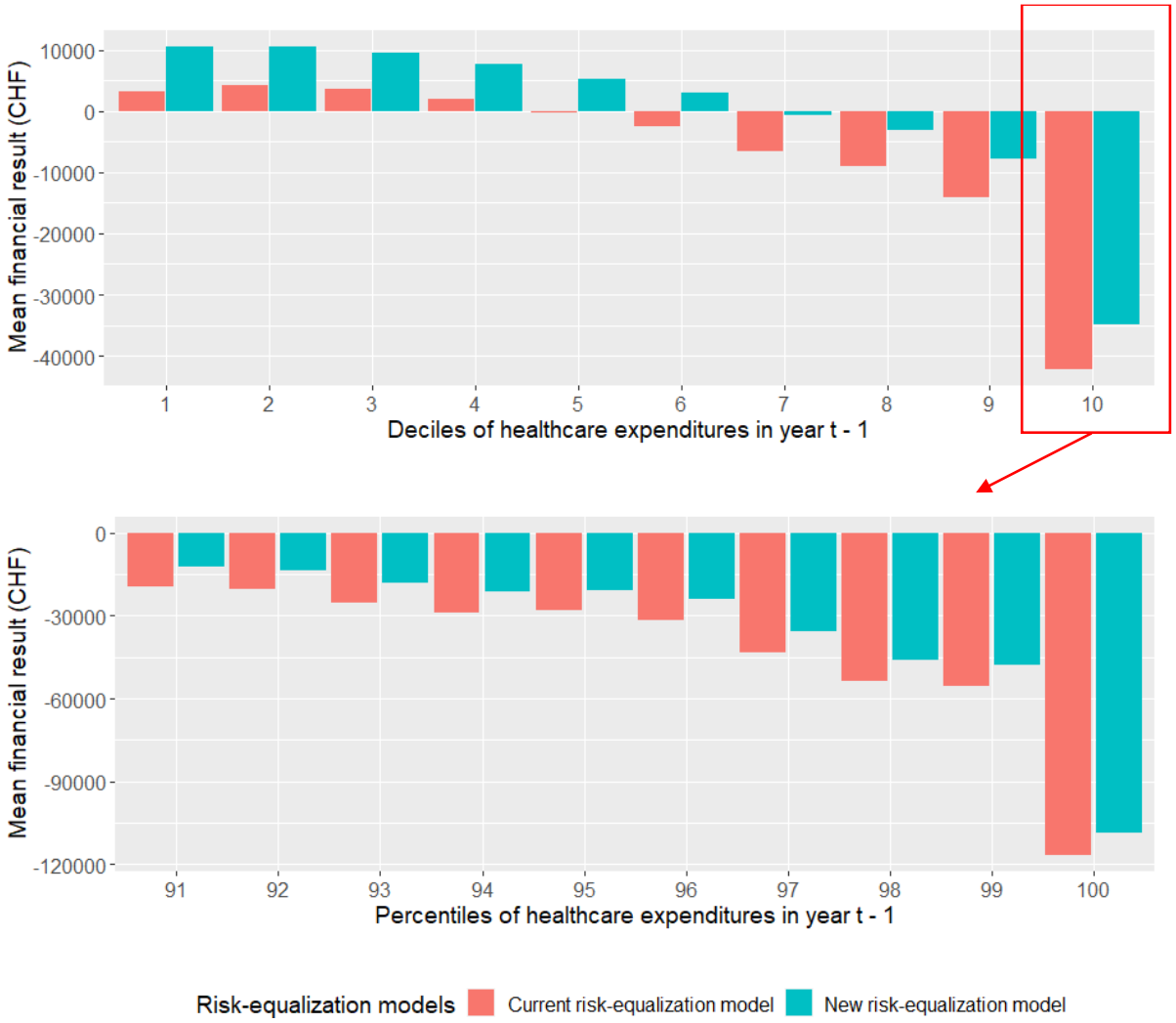
In addition to the mean financial result for the group with a high probability of dying, insight into the mean financial results of other subgroups is also gained. First, subgroups based on healthcare costs in year t – 1 are studied. Second, instead of only two subgroups, a more refined figure gives insight in different subgroups based on the predicted probability of dying.

In Figure 2 the mean financial result of the current and the new risk-equalization model are presented in a bar plot. The healthcare expenditures in year t – 1 are divided in 10 deciles/percentiles which are presented on the x-axis. On the y-axis the mean financial results are presented. The pink bar represents the current risk-equalization model, whereas the blue bar represents the new risk-

equalization model. In the top part of Figure 2 is visible that both models are equally distributed among the deciles. When comparing these bars, it is visible that for the first five deciles both risk-equalization models are overcompensating insurers for the healthcare expenditures in year t – 1. In these deciles the new risk-equalization model is more overcompensating the insurers than the current risk-equalization model does. A turning point arises in the 6th decile. In this decile the new risk-equalization model is still overcompensating the insurers, whereas the current risk-equalization model is already slightly undercompensating the insurers. After this turning point the increase in undercompensation continues for both models in last 4 deciles. In these deciles the healthcare expenditures are the highest. Visible is that both models are undercompensating insurers for enrolees with high healthcare costs. However, the new risk-equalization model is undercompensating less than the current risk-equalization model.

The 10th decile of Figure 2 is zoomed in in the bottom part of Figure 2. This part shows the highest 10 percentiles of healthcare expenditures made in year t – 1. It is visible that both models are undercompensating insurers for the healthcare expenditures in all 10 percentiles. The higher the healthcare costs, the more both models are undercompensating insurers for these high healthcare expenditures. Again, the highest healthcare expenditures, in the 10th percentile, are the most undercompensated by both models.

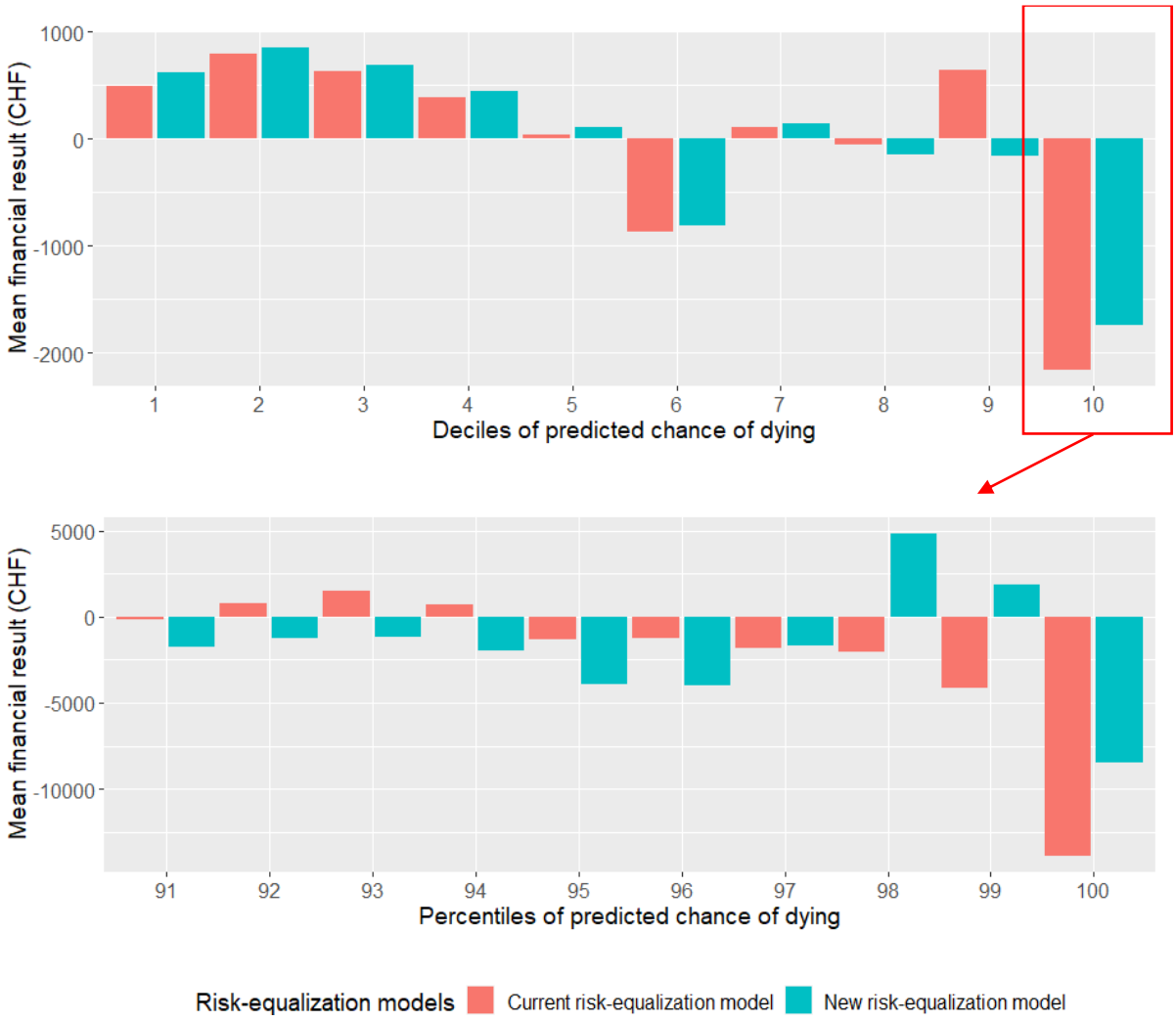
Figure 2 – Mean financial result of the current and new risk-equalization model for 10 deciles and the last 10 percentiles of healthcare expenditures in year t – 1



In part 1 of this research, the predicted probability of dying is estimated for every enrolee. Based on this predicted probability, two subgroups, “low probability of dying” and “high probability of dying”, were determined. It is also possible to divide the enrolees over more than two groups. In Figure 3, individuals are divided over 10 deciles based on their probability of dying. Figure 3 shows the mean financial result for the deciles and the highest 10 percentiles of these subgroups. On the x-axis the predicted chance of dying is divided in 10 deciles/percentiles. On the y-axis the mean financial result is presented. This figure represents the current risk-equalization model by the pink bar. The new risk-equalization model is represented by the blue bar. The top part of Figure 3 shows that the mean financial results differ between the deciles. In the bottom part of Figure 3 is visible that this difference is less widespread for the last ten percentiles. It has to be taken into account that only 3.4% of the enrolees were assigned to the group with a high probability of dying in part 1 of this section. This means that only the last four percentiles of Figure 3 represent the group “yes/no high probability of dying”. The current risk-equalization model is linear in these last four percentiles, whereas the new risk-equalization model varies more in these percentiles. Especially in the last decile it is visible that the difference in mean financial result between the two risk-equalization models is large. Both models

are undercompensating for the enrolees in this last percentile, but the new risk-equalization model reduces this undercompensation.

Figure 3 - Mean financial result of the current and new risk-equalization model for 10 deciles and the last 10 percentiles of predicted chance of dying



5. Discussion & conclusion

5.1. Main findings

This research can be divided in three parts. In part 1 the predictability of dying is researched. By using administrative information from previous years, a prediction model is estimated based on the train set. The prediction model is used to estimate the probability of dying for every individual in the test dataset. Based on this predicted chance of dying a turning point is determined which divides the dataset in two groups. One group with a low probability of dying and one group with a high probability of dying. Based on the actual percentages of deaths within the two groups, it can be concluded that the prediction model performs well. The actual frequency of dying for an enrolee assigned to the group with a high probability of dying is 30 times higher than for enrolees in the group with a low probability of dying. In part 2 of this research the current risk-equalization model is simulated by using the variables that are currently used in the Swiss risk-equalization model. From this simulation it can be concluded that enrolees with a relatively high probability of dying are on average undercompensated by the current risk-equalization model with a mean undercompensation of 6202 CHF. In part 3 of this research the simulated current risk-equalization model is extended with the new risk adjuster "yes/no high probability of dying" as a dummy variable. This dummy variable assigned a one to the group with a high probability of dying and a zero to the group with a low probability of dying. Furthermore, the two risk-equalization models are compared to each other by using three metrics for selection incentives, R^2, CPM and mean financial result. It can be concluded from all of these three metrics that the new risk-equalization model, which includes the risk adjuster "yes/no high probability of dying", compensates insurers on average better than the current risk-equalization model does. Thus, selection incentives for insurers can be reduced by including a risk adjuster based on the probability of dying.

5.2. Strengths, limitations and recommendations for further research

During the research a large dataset from a Swiss insurance company with 1.3 million enrolees has been used. Characteristics of all enrolees were adequately monitored during three years. The possibility to use this complete and clean dataset for this study is one of the strengths of this research. The access to this dataset made it possible to research the ability of risk-equalization models. This dataset is representative for the Swiss population and consists of the exact variables of the Swiss risk-equalization model which improves the reliability of this study. However, choices regarding the selection in this dataset had to be made. Only the enrolees that were available during year t, t – 1, t – 2 and t – 3 were included in the selection. That means that children that were born in year t, t – 1 or t – 2 and enrolees that deceased in year t – 1, t – 2 or t – 3 were excluded from the dataset. This selection is a commonly used method, but it may cause bias in the results of the research (Donner, 1982). As presented in the results section this selection might be the reason for the average decline in healthcare costs in the years t – 1, t – 2 and t – 3. Another possible consequence of this selection is that it might have effect on the composition of the dataset. If this selection has effect on the results, it could be interesting for further research to study the extent to which there are other possibilities to

account for the missing information of those enrolees. In this way it might be possible to deal with the missing information which could ensure that this selection does not have to take place.

Another strength of this study is the well performing prediction model. With this model it is possible to determine a group of enrolees with a high probability of dying. The actual percentage of enrolees who decease in this group is 30 times higher as for the group with a low probability of dying. This means that the prediction model is performing well which is in line with the study of Einav et al. (2018) and An et al. (2020). Despite the fact that the prediction model developed in this research is already performing well, there might be possibilities to improve this prediction model even more. In several previous studies a prediction model about the probability of dying was created by using machine learning techniques (An et al., 2020; Einav et al., 2018). It can be expected that a more advanced method like machine learning might offer more flexibility what can lead to a better prediction model. However, it is unclear to what extent machine learning algorithms can result in a better prediction model. Einav et al. (2018) and An et al. (2020) both used machine learning algorithms like LASSO and Support Vector Machine to select important variables. For future research it is recommended to use such algorithms to reduce the number of variables in the prediction model. Due to the large database, the limited time frame and the limited ability of the computer used during the research it was impossible to use machine learning techniques during this research. Although it was impossible to use machine learning during this study, it was possible to prevent potential problems with overfitting. These problems were prevented by using a validation set approach (Kassambara, 2018). With this is type of method the dataset was divided in two sets, the train and the test set. The train set, which contains a random sample of 10,000 enrolees, is only used to develop the prediction model. For the individual estimation of the probability of dying and the simulation of both the current and the new risk-equalization model the test dataset of 984,333 enrolees is used. By excluding the enrolees on which the prediction model is based in other models, problems with overfitting were prevented which is one of the strengths of this study.

Figure 1 in the result section showed a turning point which is chosen to be the boundary between high and low predicted chance of dying. This boundary is an arbitrary point in this research. By using this point, a sharp distinction could be made between the two groups which is another strength of this research. The arbitrary point could have been more to the left or the right side of Figure 1. A question for further research is how that will work out. If this point would be more to the left, there would be more enrolees with a high probability of dying than that actually decease. The average healthcare costs would be lower and this might result in a financial result which is closer to zero. On the other side, if less enrolees would be in the high probability of dying group, the average healthcare costs might be higher. The mean financial result for this group would be higher which means that there would be a higher undercompensation. In this research the new risk adjuster “yes/no highprobability of dying” is added as a dummy variable. Therefore, the estimation of the turning point is important. Nevertheless, it is unclear if adding the new risk adjuster “yes/no high probability of dying” as a dummy variable is the best way to include this new risk adjuster. There is a large variation in the group with a high predicted probability of dying. For that reason, it might be better to compensate insurers less for enrolees closer to the group with a low predicted chance of dying and compensate them more

for enrolees which have a higher predicted chance of dying. Figure 3 gives some insight in the distribution of the probability of dying. Despite some outliers upwards, the relation between mean financial result and the probability of dying is quite linear for the last 10 percentages. Hence, it might be interesting to make the consideration to add the new risk adjuster "yes/no high probability of dying" as a continuous variable or to make a division in 10 groups, the last 10 percentages for example. Nevertheless, this needs to be further researched before conclusions can be drawn.

Both, the current risk-equalization model and the new risk-equalization model are simulated. This enhances the internal validity and makes it possible to compare those models with each other. In the research it is measured that the current risk-equalization model is undercompensating insurers for enrolees with a high probability of dying. This undercompensation might lead to selection incentives which can be reduced by including the new risk adjuster "yes/no high probability of dying". However, there are three main criteria which must be met before it can be concluded that this risk adjuster is an appropriate indicator for the risk of a consumer. These are the appropriateness of incentives, fairness and feasibility (Van de Ven & Ellis, 2000). The new risk adjuster "yes/no high probability of dying" does not meet the first criterium, the appropriateness of incentives. Although this risk adjuster has predictive power for future healthcare costs and reduces incentives for risk selection, other criteria were not taken into account and this is a limitation of this research. Incentives for efficiency should have been considered (Van Kleef et al., 2015; Van de Ven & Ellis, 2000). Incentives for efficiency might decrease by adding this new risk adjuster. In the prediction model made in part 1 is visible that the healthcare costs in year t – 1 play a large role in the prediction of dying. This is in line with the literature in which is concluded that healthcare costs are high for enrolees in their last year of life (Polder et al., 2006; Stooker et al., 2001). However, the large contribution of healthcare costs in year t – 1 in the new risk adjuster means that insurers might have influence on their risk equalization contribution for next year. Indirectly the new risk adjuster creates a link between healthcare costs in year t – 1 and the risk equalization. This is an undesirable effect and might lead to a decrease in efficiency (Lamers, 1997; Lamers & van Vliet, 1996; Van de Ven & Ellis, 2000). A recommendation for further research is to investigate in researching the effect of this new risk adjuster on the incentives for efficiency.

Whether the new risk adjuster meet the second criterium, fairness, is more questionable. The risk adjuster "yes/no high probability of dying" might be a factor for which solidarity is desired, because better compensations for enrolees with a high probability of dying might increase their access to good quality healthcare. When insurers are adequately compensated for enrolees with a high probability of dying, they will no longer select against these enrolees. Nevertheless, it is difficult to make a strict division between factors for which solidarity is desired and factors for which solidarity is not desired. That is the reason why the risk adjuster differs between countries and this makes it questionable if the risk adjuster meets this criterium (Schokkaert & Van de Voorde, 2006; Van de Ven & Ellis, 2000). Therefore, it would be good to research the impact of the new risk adjuster on different risk-equalization models. For further research it would be recommended to look into risk-equalization models of different countries. In this way the fit of the risk adjuster "yes/no high probability of dying" in other countries can be explored. The new risk adjuster does meet the third criterium, feasibility.

The administrative information which was made available by the insurer was the only data that is used during the research. This means that it is possible to measure this risk adjuster without unnecessary investments of time or money. On top of that, the risk adjuster is regularly collected, valid and consist of predictive power for future healthcare costs. These norms of the feasibility criterium are discussed in the study of Van de Ven and Ellis (2000) and are all met by this risk adjuster.

5.3. Policy implications

This study shows that enrolees with a relatively high probability of dying are actually predictably unprofitable for insurers. Insurers are undercompensated for the group "high probability of dying" by the current risk-equalization model. As a consequence, insurers might get incentives to engage in risk selection. These incentives for risk selection might lead to not contracting quality of healthcare related to the final stage of life or inefficiency (Beck et al., 2020; Van de Ven & Ellis, 2000; Van de Ven et al., 2003; Van de Ven, 2011). This research shows that a new risk adjuster "yes/no high probability of dying" can be included in the current risk-equalization model as a simple measure to prevent incentives for risk selection. The implementation of this risk adjuster ensures that insurers are better compensated for the group with a high probability of dying. At the same time however, there are still questions that may need to be answered before this new risk adjuster can be implemented.

As mentioned before in this section, healthcare costs in year t – 1 have a large contribution in the new risk adjuster. The question is whether the new risk adjuster "yes/no high probability of dying" must be included while it is also possible to directly include healthcare costs in year t – 1. The problem-analysis of this research came from the risk selection problem that occurs because high healthcare costs are related to the final stage of life. A logical consequence is to decide to adjust the compensation for insurers as much as possible for the group with a high probability of dying. By directly including the risk adjuster "healthcare costs in year t – 1" the focus would not only be on the group with a high probability of dying. Not only the healthcare costs that are related to the final stage of life will be included, but also structural high costs for enrolees who are not in their final stage of life. That in turn can be disadvantageous, because insurers would have influence on their own equalization contribution and such a variable could become very important in the model (Lamers, 1997; Lamers & van Vliet, 1996; Van de Ven & Ellis, 2000). This is an undesirable effect and might lead to a decrease in efficiency. Therefore, in this case, the risk adjuster "yes/no high probability of dying" fits better in the risk-equalization model than the adjuster "healthcare costs in year t – 1", because this adjuster focusses on the group with a high probability of dying. However, it would be interesting to compare these two risk adjusters with each other in further research and take into account the purpose of the research and incentives for efficiency. The question is, what is in practice the problem that needs to be solved?

Polder et al. (2006) have found that there is a high variance in healthcare costs among the different causes of death. The variance in healthcare costs among different diseases are not researched in this study. A suggestion for further research would be to study if there are variances in healthcare costs among the different diseases and whether they have an effect on the probability of dying.

The last question is the extent to which the new risk adjuster can be translated to other countries. Several countries use a regulated competition system (Van de Ven et al., 2003). It can be assumed that similar results can be obtained when this study is repeated for the countries with such a system. It would be recommended to adhere to the three separate parts when performing analysis for other countries. The results are directly relevant for Switzerland, but only on the subgroup level. The probabilities of dying cannot be used for the individual level. For other countries, the specific results will be less relevant. This is partly due to the differences in risk-equalization models of the countries (Schokkaert & Van de Voorde, 2006; Van de Ven & Ellis, 2000). Nevertheless, the methodological innovation of adding the new risk adjuster to the risk-equalization model is interesting for these countries. This research gives insight for further research to solve the risk selection problem that occurs in Switzerland and other countries. The last recommendation for further research is to repeat and extent this research to other countries. In addition to the incentives for risk selection also the incentives for efficiency has to be taken into account.

5.4. Conclusion

A prediction model with administrative information from previous years was developed. The probability of dying for the group with a high probability of dying is 30 times greater than for the group with a low probability of dying. The group with a high probability of dying is undercompensated by the current risk-equalization system with a mean value of 6262 CHF. By extending the current risk-equalization model with the risk adjuster “yes/no high probability of dying” this undercompensation can be eliminated. Selection incentives for insurers can be reduced by including a risk adjuster based on the probability of dying. Before the risk adjuster can be included in the risk-equalization model, other criteria need to be taken into account.

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7. Appendices

Appendix A – Mean values and standard deviations for variables in the total and the train dataset

	Total dataset (N=994,333)	Train dataset (N=10,000)
Deceased in year t	0.010 (0.098)	0.010 (0.097)
Hospitalization in year t – 1	0.073 (0.260)	0.071 (0.257)
Hospitalization in year t – 2	0.067 (0.250)	0.069 (0.253)
Hospitalization in year t – 3	0.063 (0.242)	0.061 (0.240)
Women age 0-18	0.078 (0.268)	0.078 (0.268)
Men age 0-18	0.082 (0.275)	0.079 (0.270)
Women age 19-25	0.039 (0.194)	0.038 (0.191)
Men age 19-25	0.041 (0.198)	0.040 (0.196)
Women age 26-30	0.029 (0.168)	0.030 (0.169)
Men age 26-30	0.029 (0.166)	0.027 (0.162)
Women age 31-35	0.030 (0.169)	0.029 (0.167)
Men age 31-35	0.029 (0.169)	0.030 (0.170)
Women age 36-40	0.030 (0.170)	0.029 (0.167)
Men age 36-40	0.028 (0.165)	0.030 (0.169)
Women age 41-45	0.033 (0.179)	0.032 (0.177)
Men age 41-45	0.030 (0.171)	0.033 (0.178)
Women age 46-50	0.041 (0.198)	0.040 (0.195)
Men age 46-50	0.038 (0.191)	0.041 (0.197)
Women age 51-55	0.042 (0.201)	0.044 (0.204)
Men age 51-55	0.041 (0.198)	0.042 (0.200)
Women age 56-60	0.038 (0.191)	0.038 (0.191)
Men age 56-60	0.037 (0.188)	0.036 (0.187)
Women age 61-65	0.033 (0.179)	0.033 (0.178)
Men age 61-65	0.032 (0.175)	0.031 (0.173)
Women age 66-70	0.032 (0.177)	0.033 (0.179)
Men age 66-70	0.029 (0.168)	0.028 (0.164)
Women age 71-75	0.030 (0.170)	0.033 (0.178)
Men age 71-75	0.025 (0.156)	0.024 (0.153)
Women age 76-80	0.024 (0.153)	0.024 (0.152)
Men age 76-80	0.018 (0.132)	0.018 (0.131)
Women age 81+	0.041 (0.199)	0.040 (0.196)
Men age 81+	0.022 (0.148)	0.023 (0.151)
PCG in year t – 1 number 1	0.022 (0.148)	0.022 (0.146)
PCG in year t – 1 number 2	0.007 (0.083)	0.007 (0.081)
PCG in year t – 1 number 3	0.023 (0.150)	0.020 (0.140)
PCG in year t – 1 number 4	0.013 (0.114)	0.013 (0.112)
PCG in year t – 1 number 5	0.003 (0.058)	0.005 (0.067)
PCG in year t – 1 number 6	0.085 (0.280)	0.087 (0.281)
PCG in year t – 1 number 7	0.005 (0.067)	0.004 (0.062)
PCG in year t – 1 number 8	0.005 (0.073)	0.006 (0.078)
PCG in year t – 1 number 9	0.001 (0.032)	0.001 (0.032)
PCG in year t – 1 number 10	0.009 (0.094)	0.008 (0.088)
PCG in year t – 1 number 11	0.007 (0.082)	0.008 (0.089)
PCG in year t – 1 number 12	0.002 (0.043)	0.002 (0.046)
PCG in year t – 1 number 13	0.001 (0.034)	0.001 (0.033)
PCG in year t – 1 number 14	0.028 (0.164)	0.028 (0.165)
PCG in year t – 1 number 15	0.049 (0.216)	0.048 (0.214)
PCG in year t – 1 number 16	0.021 (0.145)	0.024 (0.152)

	Total dataset (N=994,333)	Train dataset (N=10,000)
PCG in year t – 1 number 17	0.032 (0.176)	0.034 (0.181)
PCG in year t – 1 number 18	0.007 (0.080)	0.006 (0.080)
PCG in year t – 1 number 19	0.006 (0.075)	0.005 (0.070)
PCG in year t – 1 number 22	0.055 (0.227)	0.055 (0.227)
PCG in year t – 1 number 23	0.005 (0.071)	0.006 (0.075)
PCG in year t – 1 number 24	0.001 (0.032)	0.002 (0.039)
PCG in year t – 1 number 25	0.002 (0.045)	0.002 (0.042)
PCG in year t – 1 number 26	0.005 (0.069)	0.005 (0.073)
PCG in year t – 1 number 27	0.008 (0.091)	0.009 (0.092)
PCG in year t – 1 number 28	0.003 (0.057)	0.003 (0.055)
PCG in year t – 2 number 1	0.023 (0.149)	0.023 (0.151)
PCG in year t – 2 number 2	0.007 (0.080)	0.006 (0.079)
PCG in year t – 2 number 3	0.022 (0.147)	0.020 (0.139)
PCG in year t – 2 number 4	0.013 (0.113)	0.012 (0.110)
PCG in year t – 2 number 5	0.003 (0.056)	0.005 (0.067)
PCG in year t – 2 number 6	0.081 (0.273)	0.082 (0.274)
PCG in year t – 2 number 7	0.004 (0.066)	0.004 (0.059)
PCG in year t – 2 number 8	0.005 (0.070)	0.005 (0.072)
PCG in year t – 2 number 9	0.001 (0.031)	0.001 (0.030)
PCG in year t – 2 number 10	0.008 (0.089)	0.007 (0.085)
PCG in year t – 2 number 11	0.007 (0.080)	0.009 (0.092)
PCG in year t – 2 number 12	0.002 (0.042)	0.002 (0.048)
PCG in year t – 2 number 13	0.001 (0.031)	0.001 (0.036)
PCG in year t – 2 number 14	0.026 (0.159)	0.028 (0.164)
PCG in year t – 2 number 15	0.047 (0.211)	0.047 (0.211)
PCG in year t – 2 number 16	0.020 (0.141)	0.022 (0.148)
PCG in year t – 2 number 17	0.030 (0.170)	0.032 (0.176)
PCG in year t – 2 number 18	0.007 (0.084)	0.008 (0.087)
PCG in year t – 2 number 19	0.006 (0.075)	0.005 (0.071)
PCG in year t – 2 number 22	0.053 (0.223)	0.053 (0.224)
PCG in year t – 2 number 23	0.005 (0.069)	0.006 (0.078)
PCG in year t – 2 number 24	0.001 (0.032)	0.001 (0.033)
PCG in year t – 2 number 25	0.002 (0.043)	0.001 (0.035)
PCG in year t – 2 number 26	0.004 (0.064)	0.004 (0.066)
PCG in year t – 2 number 27	0.007 (0.081)	0.007 (0.085)
PCG in year t – 2 number 28	0.003 (0.056)	0.003 (0.054)
PCG in year t – 3 number 1	0.023 (0.149)	0.023 (0.151)
PCG in year t – 3 number 2	0.006 (0.078)	0.006 (0.077)
PCG in year t – 3 number 3	0.021 (0.144)	0.020 (0.139)
PCG in year t – 3 number 4	0.012 (0.110)	0.011 (0.104)
PCG in year t – 3 number 5	0.003 (0.054)	0.004 (0.065)
PCG in year t – 3 number 6	0.075 (0.263)	0.078 (0.268)
PCG in year t – 3 number 7	0.004 (0.064)	0.003 (0.056)
PCG in year t – 3 number 8	0.004 (0.066)	0.005 (0.068)
PCG in year t – 3 number 9	0.001 (0.030)	0.001 (0.028)
PCG in year t – 3 number 10	0.007 (0.085)	0.007 (0.081)
PCG in year t – 3 number 11	0.006 (0.078)	0.008 (0.091)
PCG in year t – 3 number 12	0.002 (0.041)	0.002 (0.048)
PCG in year t – 3 number 13	0.001 (0.031)	0.001 (0.033)
PCG in year t – 3 number 14	0.024 (0.154)	0.027 (0.161)
PCG in year t – 3 number 15	0.045 (0.208)	0.045 (0.206)
PCG in year t – 3 number 16	0.020 (0.138)	0.022 (0.146)
PCG in year t – 3 number 17	0.028 (0.164)	0.030 (0.170)
PCG in year t – 3 number 18	0.008 (0.088)	0.007 (0.081)
PCG in year t – 3 number 19	0.006 (0.074)	0.005 (0.073)

	Total dataset (N=994,333)	Train dataset (N=10,000)
PCG in year t – 3 number 22	0.050 (0.218)	0.052 (0.221)
PCG in year t – 3 number 23	0.005 (0.067)	0.006 (0.075)
PCG in year t – 3 number 24	0.001 (0.031)	0.001 (0.033)
PCG in year t – 3 number 25	0.002 (0.040)	0.001 (0.035)
PCG in year t – 3 number 26	0.004 (0.060)	0.004 (0.065)
PCG in year t – 3 number 27	0.005 (0.071)	0.005 (0.068)
PCG in year t – 3 number 28	0.003 (0.055)	0.003 (0.057)
Healthcare costs in year t – 1	3920 (9790)	3810 (8590)
Healthcare costs in year t – 2	3540 (9010)	3590 (8790)
Healthcare costs in year t – 3	3220 (8330)	3270 (9260)

The mean values of the variables are presented in this appendix. To translate these values to the frequencies which are presented in Table 1 and 2 of this research the values must be multiplied by 100%. For example, the mean value of the variable hospitalization in year t – 1 is 0.073. This means that 7.3% of the enrolees in the dataset scores a 1 on this variable.

Appendix B – Mean values and standard deviations for all enrolee characteristics for both groups, high and low probability of dying

	High probability of dying 3,4% (N = 33.075)	**Low probability of dying 96,6% (N = 951.258)**
Deceased in year t	0.145 (0.353)	0.005 (0.070)
Hospitalization in year t – 1	0.752 (0.432)	0.049 (0.217)
Hospitalization in year t – 2	0.511 (0.500)	0.051 (0.221)
Hospitalization in year t – 3	0.383 (0.486)	0.052 (0.221)
Women age 0-18	0.001 (0.032)	0.081 (0.272)
Men age 0-18	0.001 (0.031)	0.085 (0.279)
Women age 19-25	0.001 (0.033)	0.041 (0.197)
Men age 19-25	0.002 (0.039)	0.042 (0.201)
Women age 26-30	0.001 (0.033)	0.030 (0.170)
Men age 26-30	0.001 (0.031)	0.030 (0.169)
Women age 31-35	0.002 (0.042)	0.031 (0.172)
Men age 31-35	0.002 (0.042)	0.030 (0.171)
Women age 36-40	0.002 (0.041)	0.031 (0.172)
Men age 36-40	0.002 (0.044)	0.029 (0.167)
Women age 41-45	0.003 (0.052)	0.034 (0.182)
Men age 41-45	0.002 (0.046)	0.031 (0.173)
Women age 46-50	0.004 (0.066)	0.042 (0.201)
Men age 46-50	0.004 (0.062)	0.039 (0.194)
Women age 51-55	0.008 (0.086)	0.044 (0.204)
Men age 51-55	0.010 (0.098)	0.042 (0.201)
Women age 56-60	0.012 (0.108)	0.039 (0.193)
Men age 56-60	0.021 (0.142)	0.037 (0.189)
Women age 61-65	0.012 (0.108)	0.034 (0.181)
Men age 61-65	0.008 (0.088)	0.032 (0.177)
Women age 66-70	0.016 (0.126)	0.033 (0.178)
Men age 66-70	0.043 (0.202)	0.028 (0.166)
Women age 71-75	0.012 (0.108)	0.030 (0.171)
Men age 71-75	0.014 (0.118)	0.025 (0.157)
Women age 76-80	0.054 (0.226)	0.023 (0.149)
Men age 76-80	0.068 (0.252)	0.016 (0.126)
Women age 81+	0.458 (0.498)	0.027 (0.162)
Men age 81+	0.240 (0.427)	0.015 (0.120)
PCG in year t – 1 number 1	0.072 (0.258)	0.021 (0.142)
PCG in year t – 1 number 2	0.013 (0.112)	0.007 (0.082)
PCG in year t – 1 number 3	0.025 (0.157)	0.023 (0.150)
PCG in year t – 1 number 4	0.169 (0.375)	0.008 (0.087)
PCG in year t – 1 number 5	0.017 (0.128)	0.003 (0.054)
PCG in year t – 1 number 6	0.329 (0.470)	0.077 (0.267)
PCG in year t – 1 number 7	0.021 (0.143)	0.004 (0.063)
PCG in year t – 1 number 8	0.028 (0.164)	0.005 (0.068)
PCG in year t – 1 number 9	0.006 (0.080)	0.001 (0.029)
PCG in year t – 1 number 10	0.087 (0.281)	0.006 (0.078)
PCG in year t – 1 number 11	0.023 (0.150)	0.006 (0.079)
PCG in year t – 1 number 12	0.003 (0.058)	0.002 (0.042)
PCG in year t – 1 number 13	0.011 (0.106)	0.001 (0.028)
PCG in year t – 1 number 14	0.080 (0.272)	0.026 (0.158)
PCG in year t – 1 number 15	0.184 (0.388)	0.044 (0.206)
PCG in year t – 1 number 16	0.074 (0.262)	0.020 (0.138)
PCG in year t – 1 number 17	0.045 (0.206)	0.031 (0.174)
PCG in year t – 1 number 18	0.026 (0.160)	0.006 (0.076)
PCG in year t – 1 number 19	0.002 (0.043)	0.006 (0.076)

	High probability of dying 3,4% (N = 33.075)	Low probability of dying 96,6% (N = 951.258)
PCG in year t – 1 number 22	0.200 (0.400)	0.050 (0.217)
PCG in year t – 1 number 23	0.016 (0.125)	0.005 (0.068)
PCG in year t – 1 number 24	0.002 (0.044)	0.001 (0.032)
PCG in year t – 1 number 25	0.006 (0.076)	0.002 (0.044)
PCG in year t – 1 number 26	0 (0)	0.005 (0.070)
PCG in year t – 1 number 27	0.041 (0.199)	0.007 (0.084)
PCG in year t – 1 number 28	0.001 (0.024)	0.003 (0.058)
PCG in year t – 2 number 1	0.065 (0.247)	0.021 (0.144)
PCG in year t – 2 number 2	0.007 (0.084)	0.006 (0.080)
PCG in year t – 2 number 3	0.022 (0.147)	0.022 (0.147)
PCG in year t – 2 number 4	0.157 (0.364)	0.008 (0.088)
PCG in year t – 2 number 5	0.017 (0.130)	0.003 (0.051)
PCG in year t – 2 number 6	0.318 (0.466)	0.073 (0.259)
PCG in year t – 2 number 7	0.021 (0.142)	0.004 (0.062)
PCG in year t – 2 number 8	0.034 (0.182)	0.004 (0.063)
PCG in year t – 2 number 9	0.005 (0.067)	0.001 (0.029)
PCG in year t – 2 number 10	0.048 (0.213)	0.007 (0.081)
PCG in year t – 2 number 11	0.027 (0.161)	0.006 (0.076)
PCG in year t – 2 number 12	0.003 (0.056)	0.002 (0.042)
PCG in year t – 2 number 13	0.016 (0.125)	0.0004 (0.021)
PCG in year t – 2 number 14	0.081 (0.273)	0.024 (0.153)
PCG in year t – 2 number 15	0.221 (0.415)	0.041 (0.198)
PCG in year t – 2 number 16	0.119 (0.323)	0.017 (0.129)
PCG in year t – 2 number 17	0.050 (0.219)	0.029 (0.168)
PCG in year t – 2 number 18	0.030 (0.170)	0.006 (0.079)
PCG in year t – 2 number 19	0.002 (0.048)	0.006 (0.076)
PCG in year t – 2 number 22	0.186 (0.389)	0.048 (0.213)
PCG in year t – 2 number 23	0.012 (0.110)	0.005 (0.067)
PCG in year t – 2 number 24	0.002 (0.039)	0.001 (0.031)
PCG in year t – 2 number 25	0 (0)	0.002 (0.044)
PCG in year t – 2 number 26	0.004 (0.065)	0.004 (0.064)
PCG in year t – 2 number 27	0.036 (0.187)	0.006 (0.075)
PCG in year t – 2 number 28	0.0002 (0.016)	0.003 (0.057)
PCG in year t – 3 number 1	0.063 (0.242)	0.022 (0.145)
PCG in year t – 3 number 2	0.003 (0.054)	0.006 (0.079)
PCG in year t – 3 number 3	0.008 (0.090)	0.022 (0.146)
PCG in year t – 3 number 4	0.145 (0.352)	0.008 (0.088)
PCG in year t – 3 number 5	0.019 (0.136)	0.002 (0.048)
PCG in year t – 3 number 6	0.287 (0.452)	0.067 (0.250)
PCG in year t – 3 number 7	0.020 (0.140)	0.004 (0.060)
PCG in year t – 3 number 8	0.038 (0.190)	0.003 (0.057)
PCG in year t – 3 number 9	0.004 (0.064)	0.001 (0.028)
PCG in year t – 3 number 10	0.023 (0.149)	0.007 (0.082)
PCG in year t – 3 number 11	0.033 (0.178)	0.005 (0.072)
PCG in year t – 3 number 12	0.003 (0.057)	0.002 (0.040)
PCG in year t – 3 number 13	0.010 (0.099)	0.001 (0.025)
PCG in year t – 3 number 14	0.083 (0.275)	0.022 (0.148)
PCG in year t – 3 number 15	0.259 (0.438)	0.038 (0.191)
PCG in year t – 3 number 16	0.104 (0.305)	0.017 (0.127)
PCG in year t – 3 number 17	0.041 (0.198)	0.027 (0.163)
PCG in year t – 3 number 18	0.037 (0.188)	0.007 (0.083)
PCG in year t – 3 number 19	0.002 (0.049)	0.006 (0.075)
PCG in year t – 3 number 22	0.167 (0.373)	0.046 (0.210)
PCG in year t – 3 number 23	0.026 (0.159)	0.004 (0.062)
PCG in year t – 3 number 24	0.002 (0.039)	0.001 (0.031)

	High probability of dying 3,4% (N = 33.075)	Low probability of dying 96,6% (N = 951.258)
PCG in year t – 3 number 25	0.006 (0.075)	0.001 (0.038)
PCG in year t – 3 number 26	0.006 (0.076)	0.004 (0.060)
PCG in year t – 3 number 27	0.030 (0.170)	0.004 (0.065)
PCG in year t – 3 number 28	0 (0)	0.003 (0.056)
Healthcare costs in year t – 1	29700 (32400)	3020 (6250)
Healthcare costs in year t – 2	20100 (28300)	2960 (6820)
Healthcare costs in year t – 3	15600 (25300)	2790 (6630)

The mean values of the variables are presented in this appendix. To translate these values to the frequencies which are presented in Table 4 of this research the values must be multiplied by 100%. For example, the mean value of the variable hospitalization in year t – 1 is 0.0494 for the group with a high probability of dying. This means that 4.9% of the enrolees in the dataset scores a 1 on this variable.