Decision analysis for cost benefit studies – Example: HIV test-How do we handle uncertainty of parameter estimation?

By Dr. Jürgen Becher

Before a personal insurance contract (e.g. life, disability, critical illness) can be issued, a medical risk assessment is generally performed. The insurance company tests the applicant for adverse health factors, which could increase the risk. This prevents negative selection and a situation in which substandard risks – i.e. sick persons or people with other health hazards – would be overrepresented in the portfolio and the premiums calculated on basis of a normal population would not suffice.

The first step in medical risk assessment is based on health questionnaires in the application form. If the insurer wants additional medical information, e.g. a private medical attendant report or recent laboratory tests, this will incur costs which in most countries have to be paid by the insurer. In the case of a low sum insured, these costs could easily amount to several monthly premiums. For economic efficiency, the financial benefit of the requested information therefore has to be compared to the expenses.

What are the limits for sums insured at which certain screening tests become profitable for the insurance company? This is a very important question. The benefit of having medical information increases with increasing sums insured. If e.g. a severe disease is detected before the insurance policy is issued, a later claim could be avoided.

The benefit of a medical screening test for underwriting as well as its cost are complex measures comprising from several factors. Therefore, we need appropriate calculation models for this task.

Current situation

For higher sums insured it is common for insurance companies to request medical screening information before issuing the policy, e.g. a physical examination or several laboratory values (e.g. blood picture, creatinine, cholesterol) in most international markets.

Publications on the methods for calculating the sum limits at which a medical test becomes profitable are very scarce, probably because these calculations are generally internal issues of a company. The few studies published on this topic use the term “protective value studies”. This expression reflects the view of the insurer that the value of information depends on its ability to protect him from possible financial losses.

What the published protective value studies have in common is that all are based on a very simplified calculation formula (for more details, see below). This limits comprehensibility and can lead to errors in calculation. Simplification also restricts the complexity of the problem of decision-making, which can be managed by the model and sensitivity analysis (influence of uncertain parameter estimations on the results).

Therefore, we have introduced a new decision analysis approach to calculate the profitability limits of medical screening test in underwriting. In our modelling, we put emphasis on explicit, comprehensive and intelligible presentation of influencing factors as well as on detailed analysis of the effects of uncertainty in parameter estimation on the model results.

In this article, I will present HIV testing as an example. Nevertheless, the method can easily be transferred to other medical and non-medical tests.

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Description of parameters
In order to give a better understanding of the later explanations, I would like to briefly introduce the most important parameters first.

Prevalence: Frequency of the relevant disease or the risk factor among the applicants. Often only figures on the population prevalence are available. These may be different from applicants (for more about this, see below).

Antiselection: Negative selection. Diseased or otherwise impaired persons, who know about their problem, are more likely to seek insurance cover than healthy persons. This leads to an increase of prevalence among applicants.

Sentinel effect: deterring effect. If the insurance company requests a certain medical test, then applicants who are sick and who are afraid that their disease can be detected by the test might be discouraged. This leads to a decrease of prevalence among applicants.

The relation between prevalence, antiselection and sentinel effect is schematically illustrated in diagram 1.

Sensitivity: quality attribute of medical tests. Proportion of diseased subjects who can be detected by the test, i.e. who will get a positive test result.

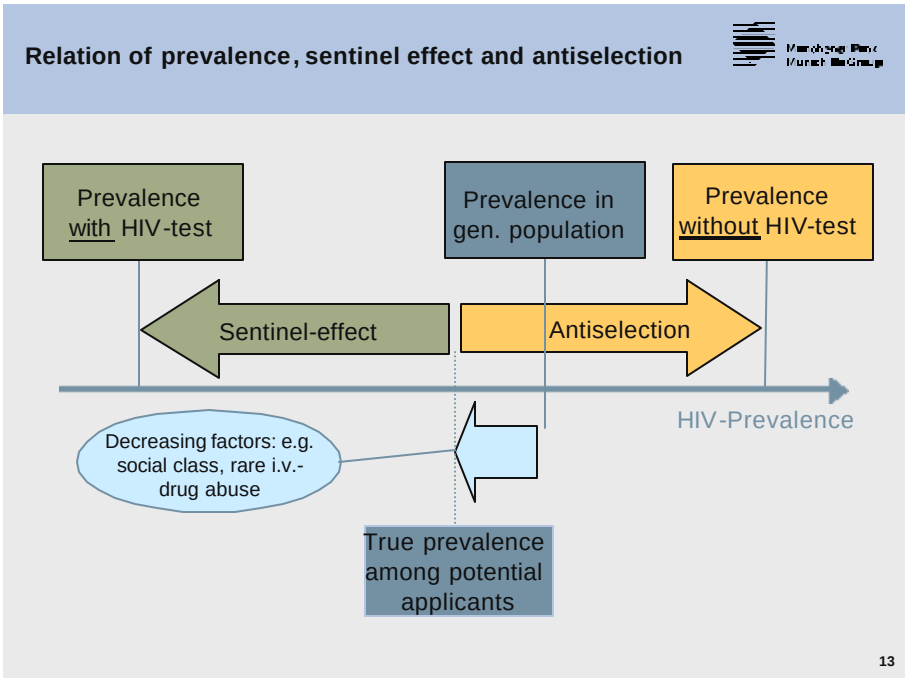
Specificity: also quality attribute of medical tests. Proportion of healthy subjects who will also qualify as being healthy by the test, i.e. who will get a negative test result.

Attribution ratio: exclusiveness of the medical test. Proportion of applicants whose disease can only be detected by this test. Vice versa: how many diseased subjects can be detected by other (cheaper) available information, e.g. questionnaires. Example: In Germany, in 1988, the question about previous HIV tests was included into the application forms for the first time. This reduced the number of AIDS-related death claims by 50% compared to policies which had been issued in the years before. Therefore, the attribution ratio of HIV tests should be well below 100% if a question about HIV tests is part of the health questionnaires.

Test costs: medical tests cost money. On the one hand, they incur direct costs, e.g. physician or laboratory fees. On the other hand, there might also emerge as indirect expenses, e.g. additional time spent by underwriters.

Mortality losses: What expenses are incurred on the average if an impaired applicant is accepted on normal conditions because the insurerer has no information about the disease? To calculate this, we have to know the probability of claims over time related to the respective impairment. Expected losses will then be discounted for the present value.

Diagram 1



Uncertainty of parameter estimation

Most of the parameters mentioned can only be estimated with uncertainty because of limited information. I want to exemplify this by the prevalence of a certain impairment.

In general there is no direct data available about the prevalence among applicants or insureds. There are two reasons for this. Firstly, most insurance companies do not record data with the high degree of detail necessary for such an analysis. Secondly, even in the case of complete records, the necessary information would not be available because the impairment is often not known at time of application (dark figure, non-disclosure). Therefore, we have to rely on data from general population studies in the virtually all cases.

For most impairments the prevalence depends on age, gender and race. Prevalence usually rises with age, e.g. in case of diabetes or myocardial infarction. The opposite is true of HIV. It affects more younger persons, because the infection is mostly transmitted by sexual contact and the risk of contracting the disease relates to sexual activity and a frequent change of partners.

But often there is no age- and gender-related data about prevalence on hand. Or there is only a very rough classification of age groups. Here we have to rely on simplifications and plausibility assumptions. In addition to this, figures on population prevalence are in many cases given only as ranges (e.g. 3 – 5%), because they also include estimations about unregistered cases.

But even if we had detailed figures on population prevalence, this would not be completely representative of applicants for life insurance. The reason for this is that potential insureds are a socio-economically selected subgroup of the population. This selections happens at several levels.

Most applicants have a job. From epidemiology, we know the so-called healthy worker effect: on the average, working people are healthier than the equivalent general population, because the latter include also subjects who e.g. are on long term care or otherwise disabled (e.g. Roos 2005)

Insurance applicants do not stem from the lowest social groups, because it is necessary to have a certain amount of disposable income that is not needed for daily living to buy insurance. From several studies we know that disease and mortality decrease with an increasing social level, e.g. because health awareness increases with education.

Some particularly exposed risk groups, e.g. drug addicts and sex workers are underrepresented as applicants for insurance. This plays a role, for example, in estimating HIV prevalence, because those groups are exceedingly exposed and, depending on the respective country, they can make up a significant proportion of HIV positive subjects. As an example, in Germany, 9% of HIV positive cases are intravenous drug users.

Especially in countries of the second world, those with upcoming industry, there is a considerable difference between the (often poor) rural and urban population in respect of disease and risk factors. Depending on the area in which the insurance company does business, such regional factors have to be taken into account.

All factors mentioned imply that prevalence and, based on comparable considerations, also most of the other parameters can only be estimated with some degree of uncertainty, in form of a range. This provokes the following questions:

How far does uncertainty influence our model results?
Which parameter has the highest impact on the uncertainty of the results?

For one case, one can then concentrate on that parameter to try to find more precise data. In general there is only limited time for research. Therefore, it makes sense to optimise resources.

Published protective value studies
There are few published protective value studies, which are all based on quite simplified formulas (e.g. Mills 1991, MIB 2003, and Bergstrom 1998a). All calculations in principle are based on a simple inequality:

Costs < Savings (1)

Starting from this, savings are calculated by simply multiplying several factors.
For example, in (Bergstrom 1998a):

"Savings/1000 = DPVB * R * (S * T + SE)" (2)

According to the publication, placeholders have the following meaning:

DPVB =	Discounted present value of future mortality loss
R =	Prevalence
S =	Sensitivity of the test
T =	Attribution ratio
SE =	Sentinel effect

This reduced model has some serious disadvantages. The underlying decision strategy is not visible. With this, on the one hand, comprehensibility is restricted. Therefore, the discussion of the method and its result are difficult and errors in reasoning and calculation are more likely to occur. On the other hand, sensitivity analysis (analysing the influence of uncertainty on the stability of the model results) is restricted, e.g. if parameters are omitted or their impact on the results has been altered by the simplification process. In addition to this, more complex models – for example if the medical test can detect several diseases, or if lost profits are to be taken into account – can hardly be managed if calculations are oversimplified.

I would like to return to the formula cited above. Normally, we would expect the sentinel effect (SE) to directly influence the prevalence, because the respective proportion of impaired subjects who are discouraged by the test will not show up for application. However, in formula (2), SE is added to sensitivity. If we now assume a sensitivity (S) of 100% and an attribution ratio (T) of 100%, then (S * T + SE) will be greater than 1, if there is any sentinel effect. This means that prevalence (R) will be multiplied by a factor which is greater than 1. With this calculation we would detect more subjects than actually exist. Perhaps this effect may be intentional, but even if this is no real error, it highly deteriorates the intelligibility of calculations. Some other factors like antiselection and specificity have simply been omitted.

It also is striking that uncertainty of parameter estimation has not been considered in the calculations of any of the studies retrieved.

Decision analysis approach to dealing with uncertainty
We used a decision analysis approach to counteract the important problem of uncertainty in parameter estimations.

Besides meta-analysis, decision analysis (DA) is one of the most important methods of desk research, i.e. for retrieving new knowledge by analysing secondary data. DA provides a basis for optimising the results of a decision after assessment of benefits, risks and costs of different action alternatives.

Practically speaking, there are especially two probabilistic methods used for DA: decision trees and markov models. Decision trees are generally used for less complex problems with a shorter time frame, while markov models are used for problems of higher complexity and a larger time frame.

In our case, we have to decide whether a screening test should be done or not. Therefore, two strategies have to be compared:

- Strategy A: requiring no medical test
- Strategy B: requiring a medical test in each case before issuing a policy

The question of the sum limits at which strategy B (test) becomes better than strategy A (no test) has to be answered from a cost perspective.

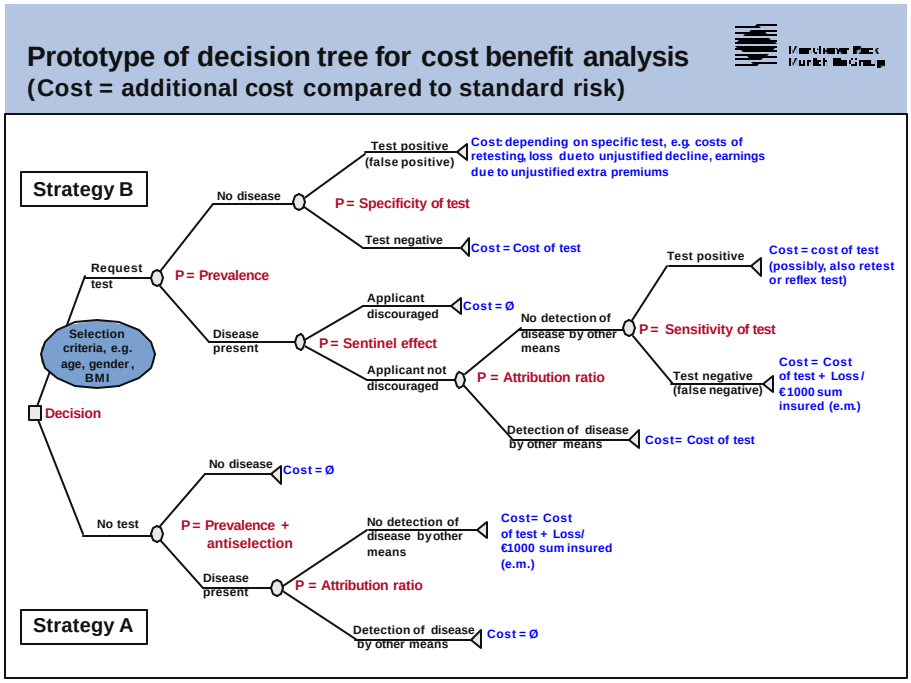
We have chosen the tree method (see diagram 2) for this decision problem, because the only calculation that has a longer time frame is the mortality experience from the portfolio. There are already established actuarial programs for modelling a portfolio. Therefore, using those tools to calculate the present value of expected losses instead of using a markov model is self-evident for this task.

In our model, only costs are considered which are caused either by the test or by diseased applicants who are accepted on a normal basis. The case of a normal risk being accepted at normal conditions is taken as zero costs. This means that there is a minimisation of losses in respect of the two action alternatives. The strategy incurring a lower loss will be preferred.

A term insurance with a 20-year policy period and a single premium was selected as the insurance product for this study.

Diagram 2 illustrates the prototypical decision tree. Depending on the specific medical test analysed, there may be small differences, e.g. instead of the branch "disease present", a more detailed differentiation, e.g. from "light" to "severe", may be necessary.

Diagram 2



Estimating model parameters for HIV testing

In order to keep the volume of this article within manageable limits and because the topic is to focus on the method rather than on the results, the description of parameter estimation will be limited to two brief examples. An overview of all parameters and their values can be found in table 1.

HIV prevalence

Prevalence estimations were based on the general Indian population. We used data from (UNAIDS/WHO 2004).

According to this publication, there are about 5.1 Million people in India infected with HIV. Average adult prevalence is 0.8%. Unfortunately, there is only a broad age classification, from 20 to 49. From other countries we know that there may be significant differences within this age span, since the age group from 20 to 30 generally has the highest risk of infection.

In India, 80% of all HIV infections are concentrated in six states. There are distinct differences between different states and regions. In one region, WHO figures on prevalence even exceed 5%.

Unfortunately, many prevalence figures in India are based on women before delivery, because this is a population subgroup which can easily be monitored. The question is whether theses data can be easily transferred to men. Since most HIV infections are caused by heterosexual contacts in India, this may be more appropriate than in other countries where homosexual contacts among men play a larger role. In such countries there is therefore a significant difference between men and women (e.g. in Germany prevalence among men is 2-6 times higher than among women).
As we have discussed earlier in this article, population prevalence might not be representative for the insured population. Due to socioeconomic selection, it can be assumed that HIV prevalence among applicants may be somewhat lower than in the general population. Some unknown factors may increase prevalence (men versus women), others may decrease prevalence (social selection). Finally, for 30-year-old men, we have applied for prevalence values from 0.5% to 2.0%. Since older people have a much lower HIV infection risk, for the age group 50, we reduced those figures by 50% (corresponding to German situation see diagram 6)

Mortality losses from HIV positive portfolios
If an insurance company accepts HIV positive applicants on a normal basis, this would incur a disprofit, because the average mortality of those subjects is much higher than the table mortality which is used for premium calculations.

The expected amount of loss was calculated by means of a Munich Re actuarial profit testing software. This program simulates an insurance portfolio for a certain product and several parameters like gender, age, and duration can be adjusted. Different interest rates, especially discount rate, are also included. For our calculations, we applied a term life insurance with 20 years duration and single premium payment. The portfolio was composed of 30-year-old male subjects. As discount rate for India we assumed 6.5%.

The actually expected mortality of the portfolio is an outstanding parameter for profit tests. This information has to be provided in terms of life tables. Therefore, mortality of HIV positive subjects had to be determined.

Mortality of HIV positive subjects
Median time from HIV infection until manifestation of AIDS (Acquired Immune Deficit Syndrome) in untreated subjects is approximately 10 years (Dietel 2003). After onset of the disease average life expectancy is not more than about 2 years. After introduction of the highly active anti-retroviral therapy (HAART) in 1997, HIV survival in highly industrialized nations has improved dramatically. Latest estimations have achieved a magnitude of about 80 to 90% mortality reduction (z.B. Sterne 2005, CASCADE 2003, Messeri 2003, Perez-Hoyos 2003). This development still seems to be unremitting.

But in India the situation is different. Until recently HAART was too expensive for a broad use among Indian HIV patients. Not until 2000 in India a new generation of cheaper medication has been developed – so called generic HAART – by which the daily cost has dropped now from 30 USD to 1 USD. According to this development the proportion of (generic) HAART treated patients did also jump up. Data from the YRG CARE center for HIV patients in Chennai, India show that there has been an increase of treatment rate among patients with incipient immune weakening (CD4 cells <200) from 5% in 1997 to over 50% in 2003 (Kumarasamy 2005). But this specialized medical center may not be taken as representative

for the whole Indian nation. On the other hand we can assume that subjects who apply for life insurance often belong to social classes who can afford modern treatment.

Apart from the unknown therapeutic situation in India, the future development of HIV mortality cannot be certainly predicted on a long term basis because the time of experience with the new therapeutic agents is still too short. There are mainly two reasons for this uncertainty:

- It is well recognized that already today HI-viruses are often resistant against the medications. In Europe about 10% of HIV infected subjects show primarily resistance , that is to say before start of treatment, against at least one antiviral substance (Das 2003). Additionally generic HAART cannot be compared one-to-one to normal HAART because the number of available substances is much smaller and especially one subgroup (protease inhibitors) is completely lacking in the generic form. This may significantly increase the risk of viral resistance in India.

- Antiviral treatment often leads to adverse reactions, which can decrease life expectancy, among them disturbance of lipid or glucose metabolism (Goebel 2001). Other possible long term sequels cannot yet be anticipated because the follow up period of published studies is still to short.

Nevertheless, according to scientific progress it can be assumed that mortality in future will probably be lower than before start of the HAART era.

Basis for our estimation of HIV mortality were figures from the time before introduction of HAART (Collaborative Group on AIDS Incubation and HIV Survival 2000). Because of the unclear future impact of modern therapy on mortality, we assumed two corner stones: reduction of mortality by 80% as minimal mortality on the one hand, and lack of any mortality reduction as maximal mortality on the other hand. As most probable estimation for India we used half the maximal 90% mortality reduction from USA and Europe (45%). Of course we investigated the model results for the complete range of mortality improvements by sensitivity analysis.

Table 1 - Overview of parameters

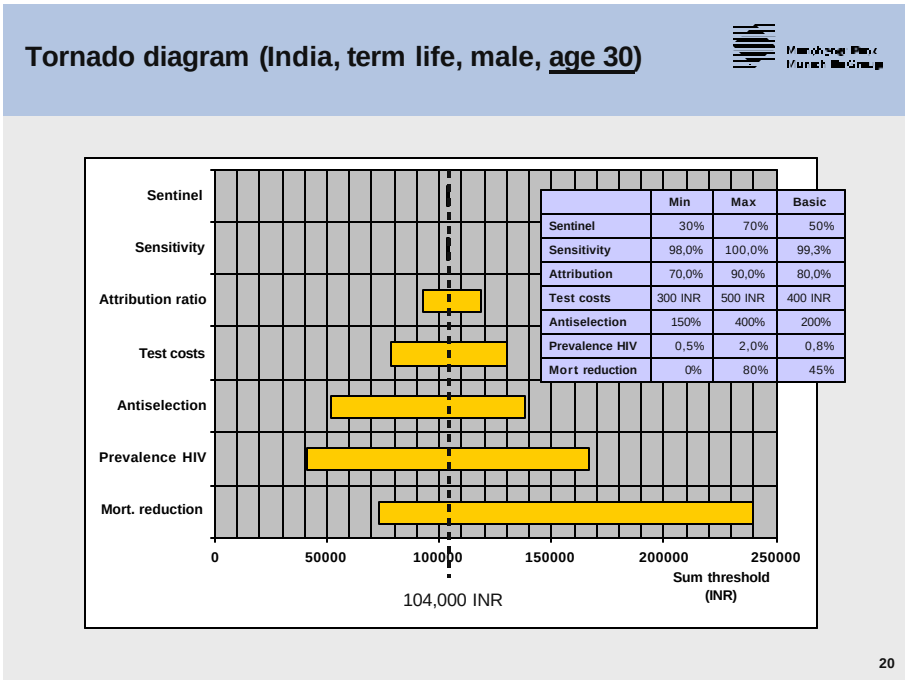
Parameter	Basic value	Uncertainty range	Source
HIV prevalence (male age 30)	0,80%	0,5% - 2%	UNAIDS/WHO Working Group on Global HIV/AIDS and STI Surveillance, Epidemiological Fact Sheet India 2004 Update
Cost of HIV test	400 RS	300 - 500 RS	Own experience; direct costs 300 – 350 INR
Sensitivity of HIV test	99,30%	98 - 100%	Own calculations based on publications of the German Robert-Koch Institute 2003 and Paul-Ehrlich Institute 2003
Specificity of HIV test	100%		Includes confirmation by Western Blot, Robert-Koch Institute 2003
Mortality losses from HIV positives (as proportion of insured sum)	0,3	0,13 - 0,425	Own calculations by actuarial profit test program. Values correspond to mortality reduction by HAART from 0 to 80%. Basic value corresponds to 45% mortality reduction
Antiselection	2	1,5 - 4	Own calculations based on Bergstrom 1998b (antiselection data), U.S. Census Bureau 2001, CDC 2001 (US prevalence and population data)
Sentinel effect	0,5	0,3 - 0,7	See antiselection
Attribution ratio	0,8	0,7-0,9	Own estimation

Results

A basic analysis for the HIV model was calculated with the basic settings of all parameters. The resulting sum threshold was 104,000 INR. This means that for a sum above this threshold the request of an HIV test would be cost efficient, in case of 30 year old male and a term insurance of 20 years.

Then for all parameters, univariate sensitivity analyses were performed. That is to say, each parameter, one after the other, has been varied within its uncertainty limits, while the remaining parameters where adjusted to their basic value. The model results of this procedure are depicted as a (inverted) tornado graph in diagram 3. Each bar on this graph represents the span of sum thresholds resulting from the uncertainty range of parameter values. We can see from this picture that uncertainty about HIV mortality has the strongest influence on the results. Depending on whether we assume a maximal therapeutic effect of 80% mortality reduction or, in contrast, no future treatment benefit effect at all, the sum threshold ranges between 75,000 INR (no effect) and 240,000 INR (maxi mal effect). Second most important is HIV prevalence, with results from 42,000 INR up to 165,000 INR. Despite its wide range of values (30% - 70%) sentinel effect has almost no impact on the results and can be neglected in this case (for explanation see conclusions).

Diagram 3



Since univariate sensitivity analysis did show several parameters which caused a wide range of resulting sum thresholds, we also included a probabilistic multivariate sensitivity analysis in terms of a Monte Carlo simulation. This method not only includes the range of parameter values but also information about their distributions. By that, the information value of calculations increases because in general not all parameter values are equally distributed. Even if we have no information about the underlying distributions, we mostly can suppose that marginal values are less probable than more centric ones. This information gets lost if we only look at intervals.

Because there is no information about the actual kind of distributions we used triangle shaped distributions.

By means of a Monte Carlo simulation parameter values have been drawn 10,000 times with probabilities according to defined distributions. A presentation of respective results is given by diagrams 4 and 5).

The median sum threshold of the Monte Carlo simulation was 68,000 INR. Interquartile range (from first to third quartile) was 50,000 to 93,000 INR. The interval from the 2.5th percentile to the 97.5th percentile, within which 95% percent of results are located, ranged from 30,000 to 165,000 INR.

The currently applied sum limits in India for HIV testing of applicants aged 30 years (recent market survey of Munich Re Group) are much higher, varying from 500,000 to 3,000,000 INR with a median of 1,500,000 INR.

Diagram 4

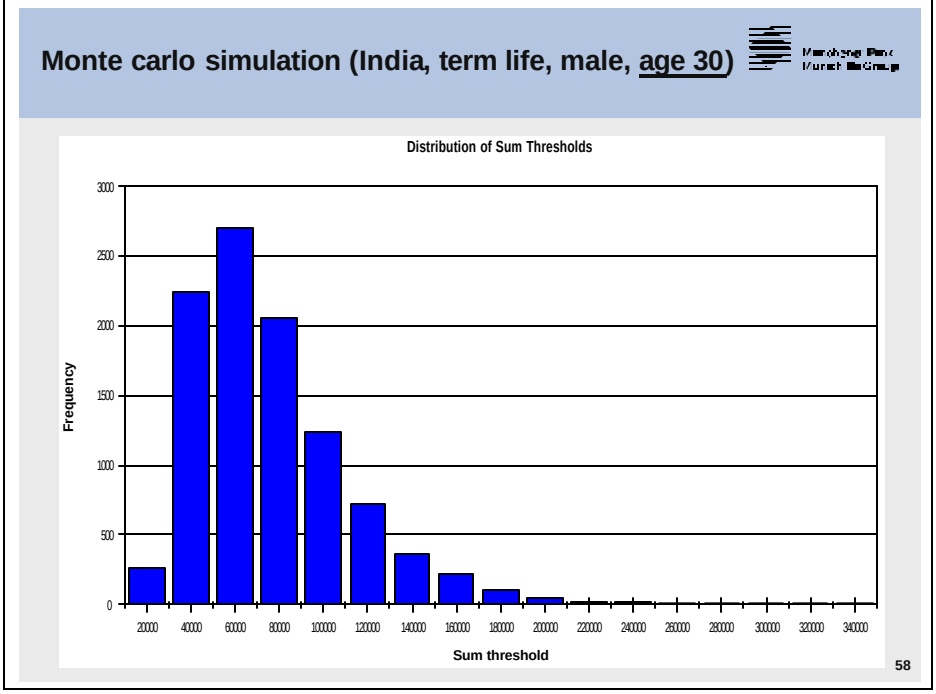
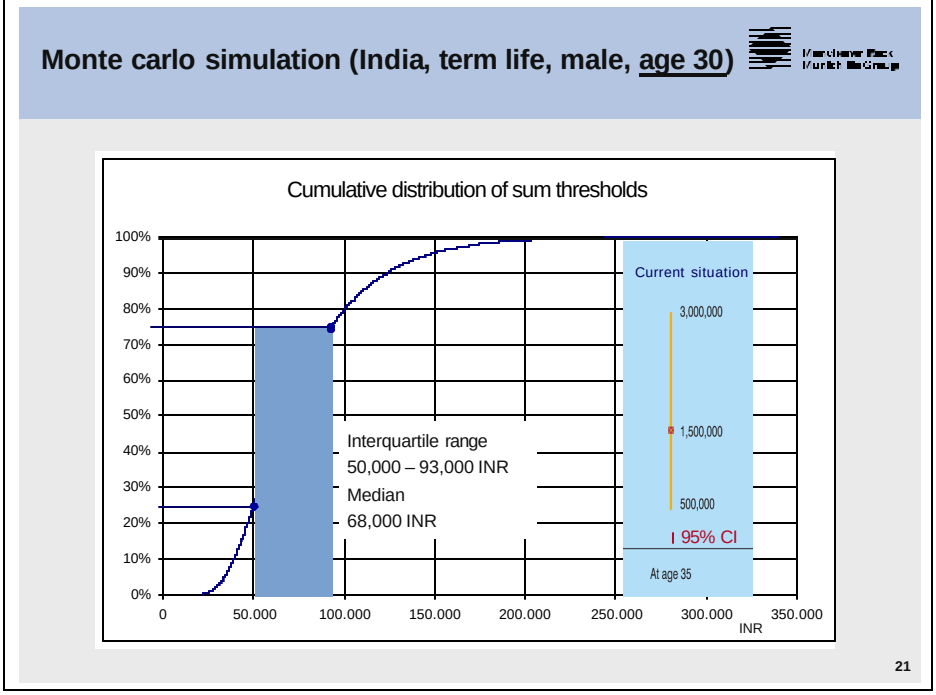


Diagram 5



Conclusions

Our results show that uncertainty plays an important role when calculating sum limits for HIV testing. The Monte Carlo study delivered a relatively wide range of results with 95% of sum thresholds lying between 30,000 and 165,000 INR. Among all influencing parameters most important are expected mortality of HIV infected subjects and their proportion among insurance applicants. This means, if we want to get more precise estimates for sum limits then we would have to try to improve our estimations with special emphasis on those two factors.

We have to keep in mind that the calculations in this article are only exemplifying one age/gender combination: men aged 30 years. In this age group we can expect the highest HIV prevalence. This means in other combinations prevalence would be lower and therefore sum limits would increase (example from Germany see diagram 6)

For 30 year old male currently applied market limits for HIV screening in India seem to be by far too high. Even the upper limit of the 95% interval of our Monte Carlo study (165,000 INR) is far away from the lowest currently applied sum threshold for HIV (500,000 INR). We also did calculations for age 50 years and found that for this age group the results (Monte Carlo interquartile range from 170,000 to 380,000 INR) by a large extent are overlapping with the actually applied market limits (starting at 250,000 INR). So for older applicants the actual market limits seem to be more appropriate.

An interesting aspect of our results is that the sentinel effect can be completely neglected. This would not have been expected based on the simplified formula (2) cited at the beginning, where sentinel effect acts as a direct multiplier on the savings. But the fact can easily be understood if we look at the general decision tree (diagram 2) and ask ourselves, when sentinel effect could play a role at all. There are only two settings where there may be considerable impact of this effect on the savings: low sensitivity of the test or high prevalence of the disease. I am going to explain this.

- Only in case that sensitivity of the respective test is low, the sentinel effect can - if it is big enough - notably increase the number of diseased applicants who are withdrawn from issuing normal policies. Only then sentinel effect can directly decrease losses resulting from increased mortality.

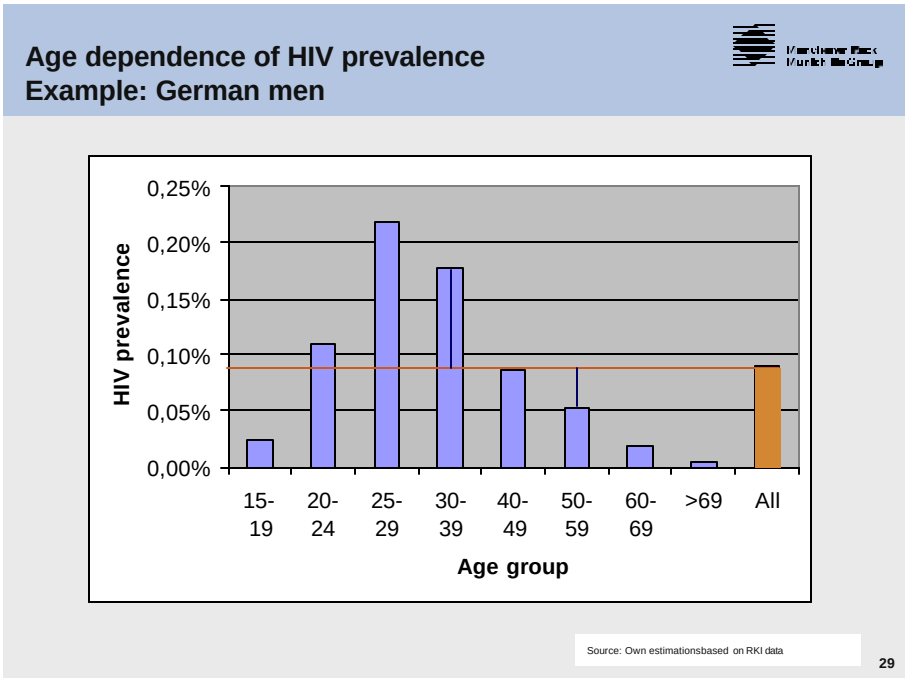
- However, if sensitivity is high (like for HIV tests), and almost all diseased subjects can be detected by the test, then the sole benefit of the sentinel effect is saving test costs. However this can only play a role if prevalence is high enough that a large proportion of test costs can be avoided. Healthy applicants (or applicants who do not know about their disease) cannot be avoided to be tested because they will not be discouraged from application by knowing about the test. In case of HIV where prevalence in most countries is (often far) below 1% the insurer always has to pay at least 99 of 100 tests irrespective of what amount sentinel effect has. So savings are very low in most circumstances.

Other general lessons we can learn from such models is that insurers can influence cost benefit limits by other means. For example the attribution ratio depends on the quality of questionnaires. The more information we can get by questionnaires the lower will be the attribution ratio of the respective test. Just remember the earlier mentioned example from Germany where introducing a question about previous HIV tests into application forms reduced death claims from AIDS by 50%.

Some other tests - e.g. metabolic lab tests like blood sugar or lipids - could be optimized by influencing prevalence. For example if in younger age groups only obese applicants would be tested – this information is mostly available at point of sale - then prevalence of elevated metabolic laboratory values would rise considerably. This would optimize both cost efficiency and positive predictive value of those tests.

Thus a comprehensive and intelligible modeling of the decision problem provides several valuable advantages.

Diagram 6



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Use of decision analysis for cost benefit studies – Example: HIV test

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8th Global Conference of Actuaries 2006, Mumbai, India

Overview

- Basic considerations
  - Risk assessment
  - Protective value studies
  - Costs and savings
  - Uncertainty
- Modelling
  - Previous approach
  - New approach
- Example: HIV test
  - Parameter estimations (brief excerpt)
  - Results
  - Conclusions

2

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Basic considerations

Medical risk assessment

- What is medical risk assessment?
  - Investigation to detect applicants with pre-existing risk factors or diseases that increase mortality
- Why medical risk assessment?
  - Balance of knowledge between applicant and insurer
  - Otherwise, substandard risks could be overrepresented (antiselection)
- Basis of medical risk assessment?
  - Medical questionnaire in application form
  - Screening tests (depending on sum insured)
  - Reflex tests and PMAR (private medical attendant report)
  - Medical tests cost money – When are they profitable?

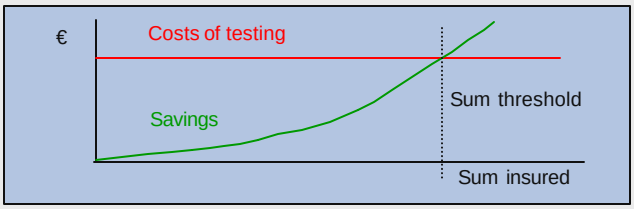
4

Written for and presented at 8th GCA, Mumbai 10-11 March, 2006

Protective value studies

Calculation to quantify the real value of a screening device

- Value of information as **protection against future loss**
- Basic requirement: **savings > costs**
- Savings increase with sum insured => **sum threshold** (savings=costs)



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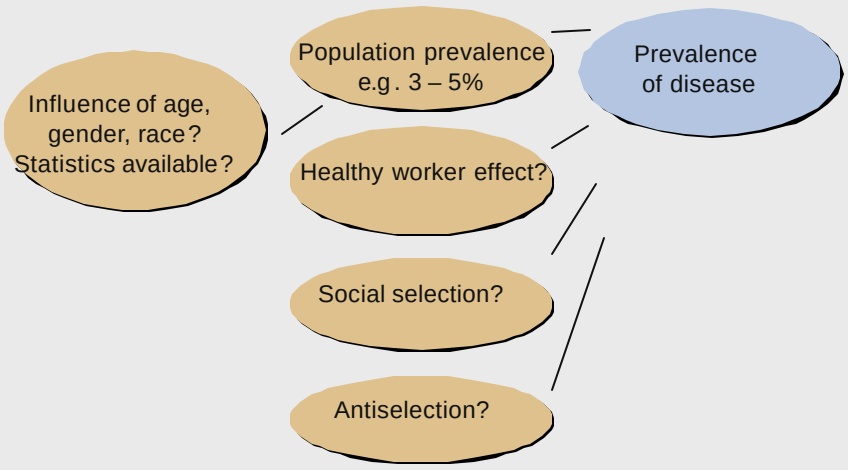
Considerations about costs and savings

Costs	What are the direct costs of the test? Are there additional costs, e.g. time for risk assessment? Profit loss due to migration of clients to competitors requiring no test? Costs from false positive test results?
Savings	What proportion of my applicants have the disease (prevalence)? Mortality of the disease (present value of future loss)? What proportion of diseased applicants can I detect with the test (sensitivity)? How many could I detect by other means (attribution ratio)? Will testing discourage diseased applicants (sentinel effect)?

Written for and presented at 8th GCA, Mumbai 10-11 March, 2006

Uncertainty of parameter estimation



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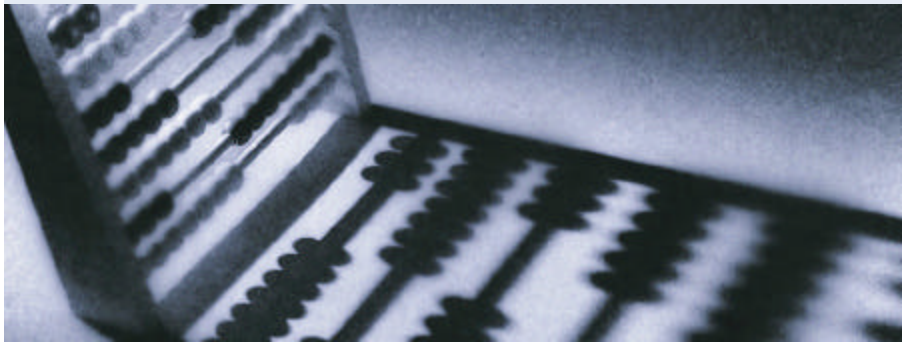
Modelling



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Previous approach

- Simple multiplication of probabilities
- Costs < savings
- Example from literature (Bergstrom):

Savings/1000 $ = DPVB * R * (S * T + SE)

DPVB =	Discounted present value of future claims
R =	Prevalence of disease among applicants
S =	Sensitivity of the test
T =	Attribution ratio (exclusiveness of information given by test result)
SE =	Sentinel effect (discourage diseased applicants)

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Previous approach

Savings/1000 $ = DPVB * R * (S * T + SE)

Problems of simplified modelling:

- Decision strategy not visible
- Very limited comprehensibility
- Susceptible to errors in reasoning and calculation
  From above example:
  - Among others, specificity is missing (intention or lapse?)
  - Multiplier of prevalence (S*T+SE) can be > 1
- Sensitivity analysis of parameters is restricted by a lack of clarity
- Complex impairments are hardly manageable

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New approach: decision analyisis

Munich Re Group

Incentives for new approach

- Explicit, exhaustive and less error-prone modelling
- Questions to be answered prior to calculating cost-benefit figures for practical use:
  - There are various uncertain parameters. **Which are most important** or critical? How high is the **impact of uncertainty** on the results?
  - Must/can we **improve** precision of some **parameter estimations**?
- Modelling decision problems of a higher level of complexity, e.g.
  - Tests relating to several diseases (e.g. blood sugar -> DM1+2, IGT, IFB)
  - Incorporation of lost profits from migration of clients to competitors

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New approach: decision analyisis

Munich Re Group

Strategy A: Requiring no test

- Negative selection
- Disease partly detectable by other means (attribution ratio)
- Mortality loss from undetected diseases among insureds

Strategy B: Test for all applicants (depending on age/gender)

- Diseased may be discouraged (sentinel effect)
- Also detectable by means other than the test (attribution ratio)
- False negative cases may pass through (sensitivity)
- Costs of testing
- How to handle false positives (specificity)?

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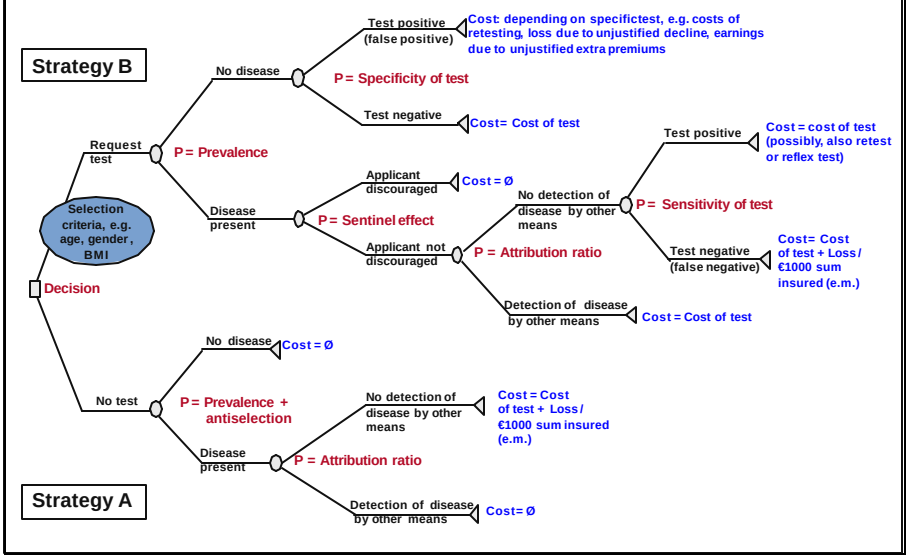
Prototype of decision tree for cost benefit analysis
(Cost = additional cost compared to standard risk)



Example: HIV test

HIV prevalence in India

- Prevalence 0.5 – 1.5 % (0.8%) - according to WHO, average for adults aged 15-49
- Heterosexual contacts are main route of transmission in India
- Sources of uncertainty:
  - Data often from **women** before delivery – Are men comparable?
  - **Regional** differences: 6 (of 35) states account for 80% of HIV cases (Andhra Pradesh (highest prevalence), Tamil Nadu, Maharashtra, Karnataka, Manipur, Nagaland)
  - No data about **socioeconomic-** and **age-**related HIV prevalence in India

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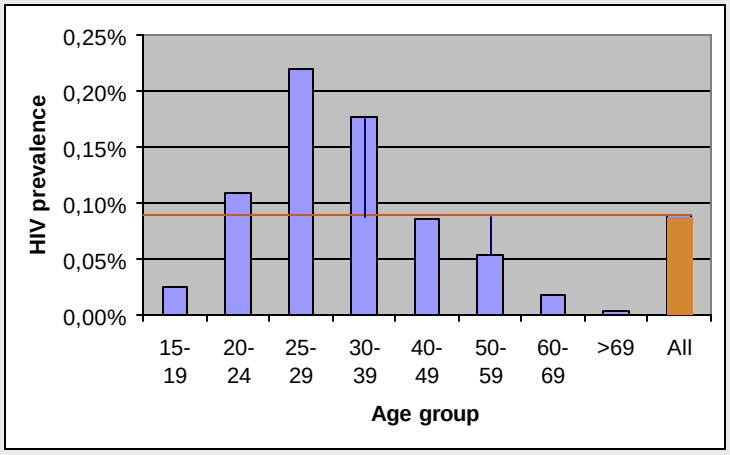
Age dependence of HIV prevalence Example: German men



Source Own estimations based on RKI data

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- 1998 - 2001 Postgraduate studies of medical biometry at the University of Heidelberg, Germany (Certified medical biometrician)
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