Capital assessment of operational risk for the solvency of health insurance companies

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Abstract Solvency II rules are expected, among other purposes, to generate a system in which the improvement of risk management, including operational risk, be rewarded to insurers through a lower charge of solvency capital. Based on a series of insured operational risk external data losses of health insurers in Spain, the authors have developed an actuarial modeling through an Operational Value at Risk analysis of the data. Results show that the model is consistent with the overall performance of operational risks and that the severity and frequency distributions adjust well to the data and ranges used in the research.

Key Words Health insurance, actuarial models, operational risk, Solvency II, OpVaR.

1 Introduction

Implementation of operational risk management has for the European insurance sector a major challenge with the new Solvency II rules (Directive 2009/138/EC), making it easier for new risk assessment models to be in line with the objectives of profitability and growth, bringing operational risk management to the most advanced corporate governance techniques. The aim of this research is to provide a measure of risk using external data from health insurers in Spain, which can facilitate benchmark studies with other departments and firms, establishing measures for their control and management.

Operational risk management, data analysis (internal and external) and its quantification have been researched in the economic and financial literature before. On the statistical analysis of operational risk, Chavez-Demoulin et al. (2005) have looked into actuarial mathematics and quantitative risk management, including operational risk. The overview of the analysis using internal data, external data and experimented valuations have been treated by Lambrigger et al. (2007), who have analyzed statistical methods and the combination of data sources for the quantification of operational risk. About VaR analysis, a well-known financial technique, see Klugman et al. (2004), who focus their research on statistical methods and on the combination of data sources for the quantification of operational risk. Other authors who have studied financial actuarial modeling for operational risk are Alexander (2001), Larneback (2006) and Chorafas (2004).

The most familiar models in financial literature for the financial analysis of operational risk are the probability models, which focus on traditional actuarial and financial calculations related to the financial and insurance industry. Of these, Value at Risk, extreme value theory and stress testing and scenario analysis models are the most used and implemented. With regard to deterministic models, Bayesian Networks stand out for their novelty and complexity of calculation, and as for econometric models, we have not found literature on its application to operational risk.

Knowing the above-mentioned situation on the current analysis and quantification of operational risk, and the clear position on operational risk models of Solvency II, we will focus on a financial analysis of operational risks of health insurers, based on a number of external data for insured losses, through a VaR analysis of the data (frequency and severity distributions), as it defines a common measure capable of universal application to a variety of risk categories and business lines. This is done because its results are expressed as a figure in monetary units, which facilitates internal and external comparisons, and the possibility of obtaining a series of conclusions on its applicability to health insurers in Spain.

The financial literature on the health insurance sector, the external databases and the quantification of operational risks has not studied all these issues simultaneously. Therefore, this research represents highly valuable information on operational risk that is fairly well suited to the quantity and quality of existing data that were available to this investigation. This is also an essential measure for determining the capital requirements for solvency for the regulator.

2 External data analysis

An external database have been used of operational risk insured losses for this research, concerning claims and incidents reported by 25 Spanish health insurance companies from 1991 to 2010, collected by an insurance broker[1]. This database is composed of about 1,350 claims of insured losses, with an aggregate value of EUR 12.3 million. It has to be kept in mind that most of these claims relate not only to incidents reported by health exclusive insurance companies, but also they include incidents that have occurred to insurers that also manage other classes of insurance. The database contains all reported losses, and the attributes recorded for each loss of the database include general information (customer reference, type of insurance class, cause and place of loss, etc.), date references and value or amount of losses.

Once we obtained the database, we proceeded to perform a thorough cleaning and treatment of it. One of the major concerns was the consistency of the data, so that each individual loss had to be initially categorized (see Table 1) according to the standard event type classification for operational risk (Association of British Insurers, 2011). Secondly, the records were classified into the following groups, given the need to model each separately because of the different nature and because of the behavior and statistical claims of each of them:

a. Damage, including multi-hazards.
b. Healthcare Liability.
c. General Liability.

[1] The database obtained for this research was agreed to be treated as confidential and not to disclose, on their own or by others directly or indirectly, disaggregated data or information to third parties.

Table 1. Loss event type classification (insurance version)

Event-Type Category (Level 1)	Categories (Level 2)
Internal Fraud	Unauthorized Activity
	Theft and Fraud
External Fraud	Theft and Fraud
	Systems Security
Employment Practices and Workplace Safety	Employee Relations
	Safe Environment
	Diversity & Discrimination
Clients, Products & Business Practices	Suitability, Disclosure & Fiduciary
	Improper Business or Market Practices
	Product Flaws
	Selection, Sponsorship & Exposure
	Advisory Activities
Damage to Physical Assets	Disasters and other events
Business Disruption and System Failures	Systems
Execution, Delivery & Process Management	Transaction Capture, Execution & Maintenance
	Monitoring and Reporting
	Customer Intake and Documentation
	Customer / Client Account Management
	Trade Counterparties
	Vendors & Suppliers

Source: Consortium database ORIC for insurers (Association of British Insurers, 2011).

An initial analysis of the database leads us to indicate that the available data matches the expected behavior of operational risk losses (high frequency/low impact and low frequency/high impact). The overall frequency of claims classified by types of events (level 1), shows a significant concentration of losses in a few events, matching the expected behavior of operational risk losses (Tripp et al., 2004). Losses are mainly concentrated in 'Damage to Physical Assets' and 'Execution, Delivery & Process Management', which accumulate 45.2 percent and 40.7 percent of the total losses, respectively. The biggest 'Damage to Physical Assets' claims are made by median cost per claim losses, which is reasonable given that most investments in physical assets of these companies are in buildings and equipment (Hernández, 2007), for example, damage to facilities and windows produced by the use and activity, water leakages or the weather conditions. It is also observed that the number of claims in ‘Execution, Delivery & Process Management’ category is high, which relates mainly to liability claims for medical interventions, which is the major activity of their business, such as medical errors, misdiagnoses, medical negligence or improper treatment. With respect to the severity of losses, exposure is more concentrated in one type of event than the frequency of losses, ‘Execution, Delivery & Process Management’, which accounts for 79.9 percent of the loss amounts, because there is a high average severity per claim, since this category includes the more serious damages mainly due to its nature, as explained above. ‘Damage to Physical Assets’, on the other hand, has a much lower rate of severity (5.2 percent).

Moreover, additional to the initial review of each entry in the database (amounts, concepts, causes, etc.) and their classification into types of events, the following adjustments were made (Jordan et al., 2003):

a. Some records were reallocated, since being medical malpractice claims, they are not considered in the database in the group Healthcare Liability.
b. Regarding the filtering of data, some records were eliminated of incorrectly open files, included in the category Cancelled from the field Situation.
c. Claims have been identified that are not covered by the insurance policy, using the fields Status from the records and Comments.
d. From the available fields (Compensation, Estimated Compensation, Total Incident and Franchise), and depending on the status information (Liquidated, On Valuation, Arranging Allowances, etc.), we obtained the total cost of claims where information was lacking.

e. The calculation of the total cost was made by using, under a conservative approach, historical data of the Industrial Price Index in Spain (National Statistics Institute of Spain, 2011).

f. Although there is a large number of years with claims data, the specific terms of coverage and risk exposure (such as capital and insured limits of each insurance contract), are not known, conditions that often change in the annual renewals of the policies to include new goods for business growth, mergers or acquisitions. For this reason, we used a tighter period (2005-2009) in which it is assumed that no significant changes in such covers and risk exposures occurred.

Furthermore, the following additional assumptions about the data were made:

a. Franchised claims:
    i. In those records with status Damages Under Franchise, given the lack of cost data in all cases, it has been assumed that the cost is equal to the franchise.
    ii. It is assumed that one out of four claims with cost under the franchise is reported to the insurers.
    iii. Given the lack of cost data under the franchise, a Pert model with parameters 0 (minimal cost), excess of 50% (cost plus probable) and franchise at 100% (maximum value) was used.
b. Claims not covered:
    i. All files with status No Consequences were considered as cases not covered by their respective policy.
    ii. Records canceled with a different cause of an error are considered as not covered.

iii. It is assumed that one out of two claims not covered by insurance is declared to the insurers.

iv. In the absence of data on claims not covered by a policy, claims covered data have been used to adjust a theoretical model, but taking only those costs within an interval equal to one standard deviation around the mean. This assumes that the risks covered and not covered are similar around their average costs.

Finally, the sample remaining after filtering presented in Table 2, consists of 380 claims for insured losses, with an aggregate value of EUR 5.6 million.

Table 2. Sample after filtering the database

Year	Number of claims	Total cost	Average cost
2005	88	618.101	7.024
2006	62	836.098	13.485
2007	73	988.811	13.545
2008	75	965.527	12.874
2009	82	989.487	12.067
Total	**380**	**5.620.102**	**14.790**

Source: Compiled by the authors

3 Quantification of operational risk of health insurers

From the study of models used in the financial literature for the actuarial financial analysis of operational risk, see summary in Table 3, it can be deduced that the models used are the probabilistic ones, which are more linked to financial and actuarial calculations traditionally associated with the financial and insurance sector. Of these, it could be highlighted VaR, extreme value theory and "scenario analysis" models, as the most common and easiest to implement in practice (Embrechts and Neslehova, 2006). As for deterministic models, Bayesian networks stand out for their novelty and complexity of calculation, and regarding econometric models, no literature was found on its application to operational risk.

Table 3. Models for the actuarial financial analysis of operational risk

Category	Models	Comments	Modelling use / References	Date of models
Probabilistic models	Severity and frequency models (statistical distributions): LDA	Very common models	Umea Un.Sweden - Frachot, Georges & Roncalliy, Crédit Lyonnais - Dutta&Perry, Federal Reserve Bank of Boston - Böcker&Klüppelberg, Munich Un.of Technology	2006
	Extrem Value	Very common models and extreme loss data is needed	Embretchs, ETH Zurich - Umea Un.Sweden - Cruz, M. - Carrillo, UAM	2007
	OpVaR	Classical model, it is a reference for Basel II and Solvency II	Umea Un.Sweden - Feria&Jiménez, Universidad Pablo de Olavide - Tripp, Watson Wyatt	2006
	Stocastic processes: Ruin theory, credibility, copula, …	Interesting to use, some are complex, such as copula	Embretchs, ETH Zurich - Brandts, Goethe Un. Frankfurt - Hult, University of Copenhagen	2005
	Other models: Stress testing, scenario analysis, DFA,…	They are commonly used in risk management, practical and simple	Embretchs, ETH Zurich - Cruz, M. - International Assotiation of Insurance Supervisors	2002
Deterministic models	Econometric models	They are commonly used, have been used for catastrophic risks and not easy to define	Not found literature on its application to operational risk	N/A
	Nonlinear models:bayesianas neuronal networks	Very complex and requires large amounts of data	Y.Khuen, City Un. London - Shevchenko, CSIRO - Wüthrich, ETH Zürich - Cruz, M. - Klugman, Panjer & Willmont	2003

Source: Compiled by the authors

Therefore, given the current state of research and a clear position on operational risk models for Solvency II, it is proposed to apply the classical VaR, as it defines a common measure of universal application susceptible to a variety of risk categories and business lines. This is done because its results are expressed as a figure in monetary units, which facilitates internal and external comparisons, and can obtain a set of conclusions on their applicability to health insurance companies.

3.1 Severity and frequency distributions

In this first stage of the methodology process, the different probability distribution models are adjusted to the historical series of operational losses broken down by categories. That is, we have tried to find the parameters of the probability distribution that best fit into the database used. Although it could be established a priori, based on experience, that some models of distributions are the most suitable when modeling the severity, in practice no simple distribution is often satisfactorily fit to the data, hence the need to make use of a combination of several distributions.

Table 4 summarizes the probability models adjusted to the cost of losses using historical data. It includes the p-value obtained from the $\chi 2$-square test to measure the goodness of fit of the competing distribution for severity to the data. Since the claims behavior is different for claims of greater amount, in all insurance classes claims data have been separated into two ranges to better align the distributions. This table shows the goodness of fit for each cost range and type of model selected for competing distributions for severity.

Table 4. Probability models adjusted to cost data losses

Insurance class group	Cost range	Distribution	p-value
Property	Under EUR 350	**Normal**	**92%**
		Lognormal	75%
		Extreme value	84%
		Inverse Gauss	79%
		Exponential	81%
	Over EUR 350	**Lognormal**	**91%**
		Normal	65%
		Extreme value	61%
		Inverse Gauss	85%
		Exponential	71%
Healthcare Liability	Under EUR 1,700	**Extreme value**	**74%**
		Normal	58%
		Lognormal	49%
		Inverse Gauss	61%
		Exponential	60%
	Over EUR 2,000 (1)	**Inverse Gauss**	**92%**
		Normal	72%
		Lognormal	84%
		Extreme value	69%
		Exponential	88%
General Liability	Under EUR 1,700	**Exponential**	**66%**
		Normal	62%
		Lognormal	46%
		Extreme value	59%
		Inverse Gauss	60%
	Over 2,800 (2)	**Lognormal**	**73%**
		Normal	57%
		Extreme value	53%
		Inverse Gauss	69%
		Exponential	53%

(1) Given the impossibility of an acceptable fit between EUR 1,700 and EUR 2,000, under EUR 2,000 the lower range model is assumed.

(2) Under EUR 2,800, the lower range model is assumed.

The following paragraphs will present and explain the figures of the probability distributions of each of the adjustments made for each interval of estimated cost. In order to understand these figures, black shows the historical cumulative probability distributions, and gray, the adjusted theoretical probability distributions. In general, it can be noticed that the greater proximity between the lines of the above-mentioned distributions, the higher the level of fit between the historical and theoretical distributions.

Figures 1 and 2 represent the probability distributions of the adjustments made for the Damage class data, for cost intervals under EUR 350 and over EUR 350 cost per claim. The models that best fit into the historical data are Normal and Lognormal distributions, both exceeding 90 percent. The parameters used in the models are shown above the figures, and they are the means and standard deviations of the severity in the period considered. The x-axis shows the value of claims incurred during the period considered, and the y-axis, the cumulative percentage. For example, in figure 1, the average severity is EUR 253.77 and the standard deviation is 71.65.

Figures 3 and 4 show the probability distributions of the adjustments made to the Healthcare Liability class data, for the cost ranges between EUR 1,700 and EUR 2,000 per claim cost. Given the impossibility of an acceptable fit between EUR 1,700 and EUR 2,000, the model assumed is the one with the lower range up to EUR 2,000, resulting in a lower goodness of fit. Cost ranges under EUR 1,700 and over EUR 2,800 per cost claim of the General Liability class are shown in figures 5 and 6.

For risks that are not covered by insurance, adjusted models to cost payment data were used. To perform this analysis, the sample was chosen from an insurer's database, as the most representative and the one that had a series as complete as possible, but considering only those included in an interval of 1 standard deviation around the average cost.

The models derived from the aggregate probability distributions for loss severity without coverage, are presented below. Figures 7, 8 and 9 show the probability distributions of the adjustments made for losses not covered by the various classes of the sample. The model that best fits the historical data is the Inverse Gauss, as seen in the charts because of the proximity between the lines of historical and theoretical distributions. Above the figures, in brackets, are shown the parameters used in the models, and these are the mean and standard deviations of the severity in the period considered. The x-axis shows the value of claims incurred during the period considered, and the y-axis shows the cumulative percentage.

To model the number of accidents that could be present to an insurer, a Poisson distribution was proposed, because is a standard for frequency estimations and we consider that the loss data has no contagion effect or influence upon the others at risk, whose parameter will be estimated from historical claim data for that company. Or, in the case of not having enough experience or base data, it could be used the average rate recorded in the database, weighted by a factor of exposure as it would be the premium.

To estimate the frequency of General Liability and Healthcare Liability classes of risks, the statistical method Chain Ladder was used, applying the proportionality parameters (factors of development) from General Liability market statistics in order to consider the nature of these risks in terms of the emergence of claims. In order to perform the calculations, a single insurer claims data, that were thought to be sufficient for the estimates, was considered. To estimate the frequency of claims in each cost interval, the average claims of the company were weighted with the proportion of records of the entire database figures in this cost range. The parameters used in the Poisson models are the average frequencies in the period. The frequency distributions used for different insurance classes included in the analysis are shown and explained below.

The adjustments of the claims frequency models (Poisson) used for each range, is shown in Figures 10 to 15 for each class and range. The figures are represented in a bar chart; above the chart are shown the parameters used in the Poisson models, which are the average frequency in the period. The x-axis shows the number of claims incurred during the period and the y-axis, their relative frequencies. For example, in Figure 12, the average rate is 0.93561, i.e. almost an incident per year, with a 90 percent probability of three or fewer claims occurring.

Figures 14 and 15 are also represented by a bar chart. In Figure 14, the average rate of 0.85417, i.e. almost a claim per year, with a 90 percent probability of three or fewer losses occurring, and in Figure 15, something similar occurs, the average frequency is about an incident a year, with the same probability of three or fewer claims occurring.

3.2 Operational risk capital assessment

Within the context of the Solvency II regulation (Hernández and Martínez, 2010), and as summarized in the introduction of this research, the aim is to analyze, from a practical point of view, the risk management of health insurers, with particular attention to operational risk and a clear focus on its application in the business environment. This deepens into the statistical analysis of operational risk health insurers, based on a number of external data of insured losses, low and medium severity and frequency and analyzing it through the methodology OpVaR of data, thus obtaining the required solvency capital.

Once the process of data collection has been developed, statistical description and processing of the operational risk losses database performed, and, finally, the severity and frequency distributions[2] identified, we proceed to obtain the aggregated loss distribution by combining both distributions through a Monte Carlo simulation approach, using the software @RISK[3] to develop a model of calculation that includes:

a. Claims reported by health insurers to their insurance companies for this type of operational risk losses under the coverage of insurance policies or contracts.
b. Claims under franchise not reported to the insurers.
c. Claims not covered or excluded from coverage in the insurance policies.

The Monte Carlo simulation performed the risk analysis by building models of possible results by substituting the range of values from the data, the probability distributions, for any factor that has inherent uncertainty. It then calculates results over and over, each time using a different set of random values from the hypothesis and probability functions mentioned above in the research, involving thousands of recalculations before it was completed, producing distributions of possible outcome values. Once the results for each scenario have been collected, the frequency histogram is complete and OpVaR is determined from the aggregated loss distribution. Monte Carlo simulation is particularly valid for our external database of operational risk losses of health insurers,

[2] At this stage in the process methodology, discussed in the previous paragraph, we tried to find the parameters of the probability distribution that best fitted the database used.

[3] @RISK is a risk analysis software tool based on Microsoft Excel spreadsheet that is commonly used for risk analysis and modelling of losses in the insurance sector using Monte Carlo simulation.

and it has allowed us to model the behavior of variables that are different from normal distributions, such as the Lognormal or the Extreme Value.

The concept of VaR operational risk (OpVaR) examines a percentile[4] of a distribution of losses caused by operational losses or failures. OpVaR can be defined as an amount, expressed in monetary units, which provides information on the minimum potential loss that might incur in a given area of business or enterprise operational risk within a given time and at a certain level of statistical confidence. One of the main specifications for the correct definition of OpVaR is the statistical confidence level, which generally depends on the risk aversion degree of each entity. In the research, the confidence level used was 99,5% over a one-year period, suggested by Solvency II (article 101) 'in order to promote good risk management and align regulatory capital requirements with industry practices'. Thus, to obtain the operational risk VaR, the total cost incurred by the company was estimated as the sum of the costs in excess of claims covered by insurance and the costs incurred by the company for not being insured or covered by the insurance contract. The calculation model developed is based on assumptions and probability distributions shown in the preceding paragraphs.

- Hypothesis. The data has been properly cleansed and treated, first classifying them accordingly to the ORIC insurance standard for the classification of events type for operational risks, categorizing the losses in terms of their nature and their statistical behavior, and making other adjustments and assumptions for filtration and elimination of inconsistent data.

[4] A percentile is the value that divides an ordered set of statistical data so that a percentage of the data is under that value.

- Probability distributions. At this stage of the methodology, different probability distribution models have been adjusted to the historical series of operating losses, being the probability distributions Normal, Lognormal, Inverse Gaussian, Extreme Value and Exponential as most were in line with the historical data of loss costs (severity), and Poisson for modeling the number of claims (frequency).

Finally, the calculation of OpVaR is immediate. The percentile for the aggregate loss distribution has to be calculated by combining the severity and frequency distributions, and depending on the selected confidence level, in our case 99.5% abovementioned, amounting to approximately EUR 856,772.30, see Figure 16, which would be the solvency capital for operational risk of that hypothetical health insurer with average reported claims obtained from the external database used in the research. The applications for insurers of the presented analysis goes beyond any figure obtained as a result, and it is focused to overcome the problem of the lack of suitable loss data for the modeling of operational risk, since Solvency II requires insurers to complement its internal loss data with some more information, mainly external data, using assumptions such as the distributions and VaR calculations suggested in this paper, to verify the calibration of the internal model and to check that its specification is in line with generally accepted market practice, which will help management for the better understanding and control of operational risk.

4 Conclusions

Insurance companies face many risks which need to be managed, but the complexity of these companies comes from the nature of their operations, that is to accept the risks underwritten by other entities or individuals, hence the strategic importance for citizens and governments that insurers protect their assets and income and to develop policies and scientific methods or structures that guarantee a minimum financial solvency and continuity of operations.

Operational risk is increasingly important in the management and corporate governance of insurers and, by extension, of health insurers. The different operations and processes of these organizations increasingly have greater implications and interactions with other risks they face, such as market or credit risks. The management and financial analysis of operational risk is a necessary activity for the insurers, which presents ample opportunities for development and a large field of study on conceptual and practical issues because of the particularity and complexity involved in these types of risks. The new Solvency II regulation has inevitably increased the need for effective management of operational risks and the development and implementation of methodologies for its analysis. Without a doubt, the focus of classical modeling technique VaR is the model that most approach their goals and provide more possibilities with respect to other methodologies, since it is a simple, reliable, well known and easily applicable. In addition to the Solvency II and Basel II benchmark, there is a clear disposition toward the VaR model for actuarial financial analysis of operational risk, though this two regulations abovementioned also indicate that other inputs should be used in the assessment of the solvency capital, like Scenario Analysis or Key Risk Indicators.

The problem of the lack of internal data for financial analysis of operational risk is well known. This is the reason why that the type of data has been used, with incidents with sufficient historical background of low and medium frequency and severity (avoiding possible results of the external databases that are usually very biased towards events of high severity and low frequency). This could help to fill this gap in the insurance industry, with its provision of operational risk data combined from several insurance companies in the sector, ranked by the types of most likely hazards and treated according to the needs of the final goals. Here is where the OpVaR provides greater value, since it defines a common measure capable of universal application to a variety of risk categories and business lines, and because its result is expressed as a figure in monetary units, which facilitates the establishment of internal and external comparisons and the possibility to set limits to control them.

As for the results of the actuarial analysis conducted on operational risk insurers in the health sector in Spain, they show that, on the one hand, the type and structure of available data (losses or claims of low and medium severity and frequency) are consistent with the general behavior of operational risks. On the other hand, with respect to the models of probability distributions of loss for the time series data, the selected distributions (Normal, Lognormal, Inverse Gaussian, and Extreme Value exponential frequency and severity Poisson), are known and commonly applied in this type of statistical work, and they have adjusted well to the data and ranges used in the research.

Finally, it should be considered that, to measure different levels of risk, it is not so relevant to reach a precise quantification of them, but to assess whether the amount is adequate for the entity being analyzed, i.e., the main objective is to control risks, above the methodologies used for measurement and analysis.

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Figures

Figure 12. Health liability. Frequency distribution, cost interval < 2.000 €

Figure 13. Health liability. Frequency distribution, cost interval > 2.000 €

Figure 14. General liability. Frequency distribution, cost interval < 2.800 €

Figure 15. General liability. Frequency distribution, cost interval > 2.800 €

Figure 16. Aggregated loss distribution, 99.5% VaR

Figure 1. Property. Severity distribution, cost interval < 350 €

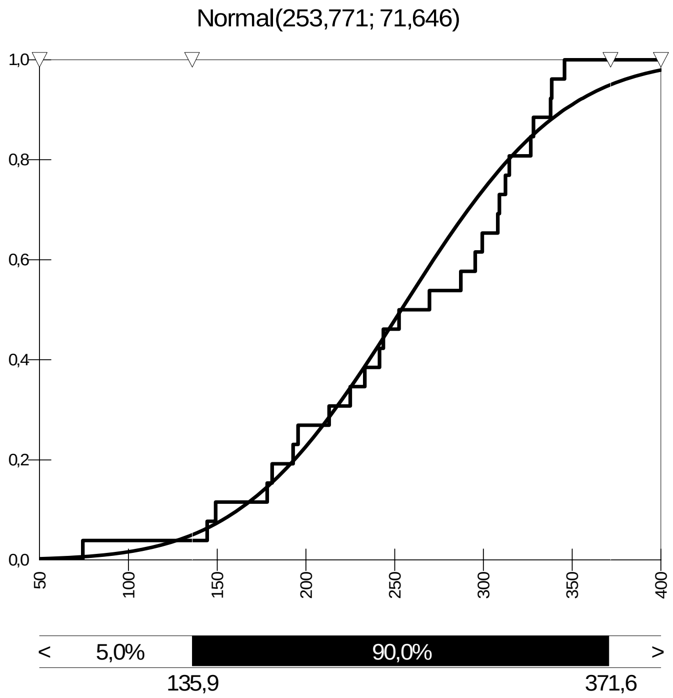

Figure 2. Property. Severity distribution, cost interval > 350 €

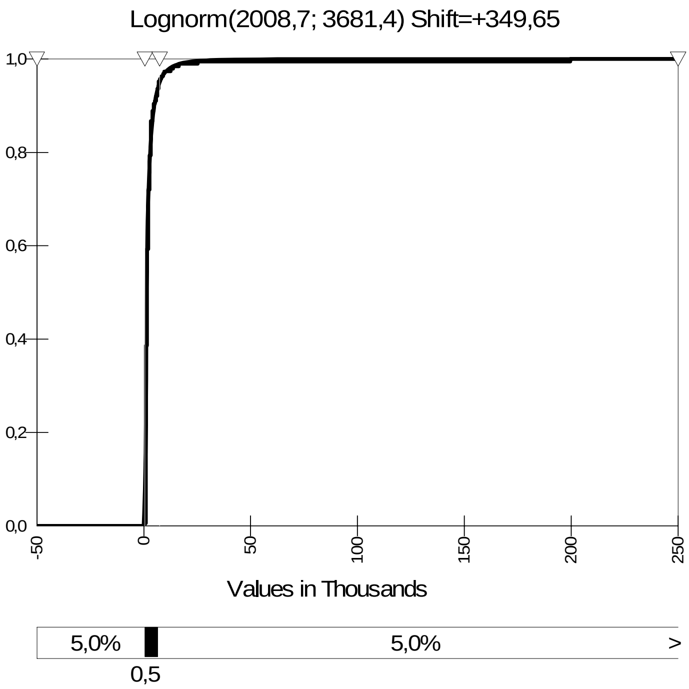

Figure 3. Health Liability. Severity distribution, cost interval < 1.700 €

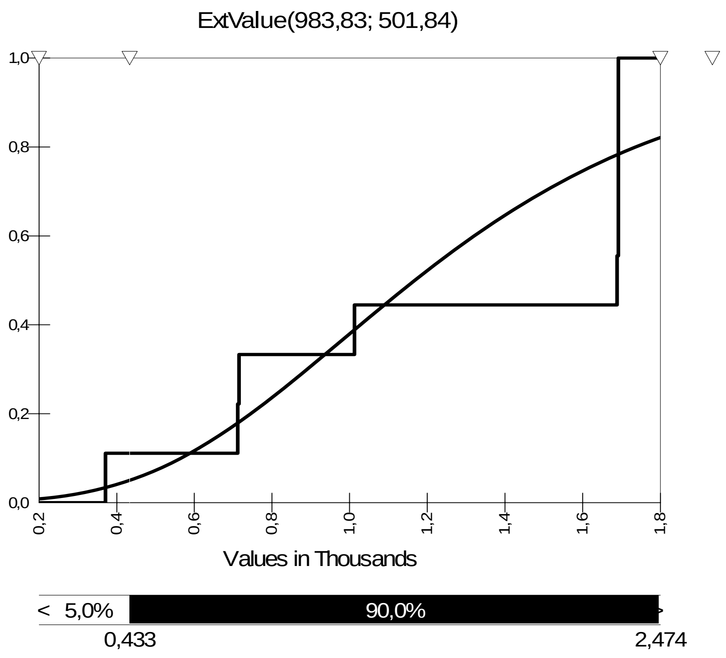

Figure 4. Health Liability. Severity distribution, cost interval > 2.000 €

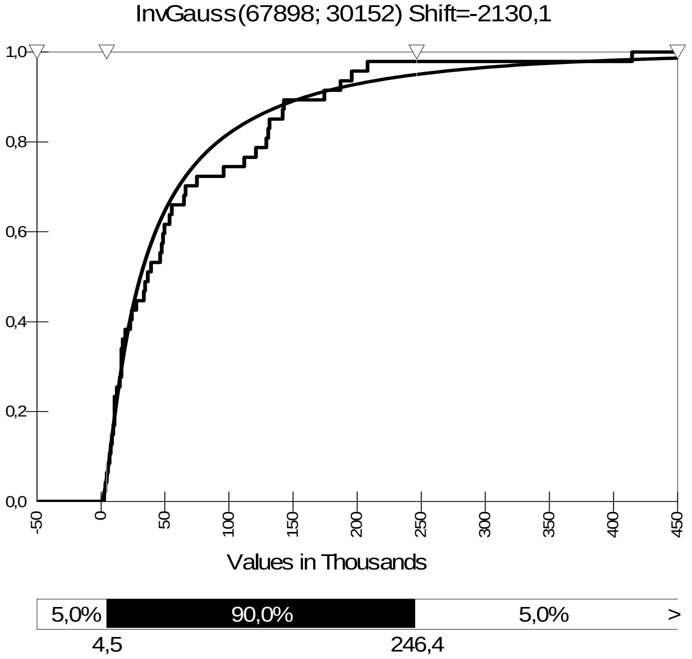

Figure 5. General Liability. Severity distribution, cost interval < 1.700 €

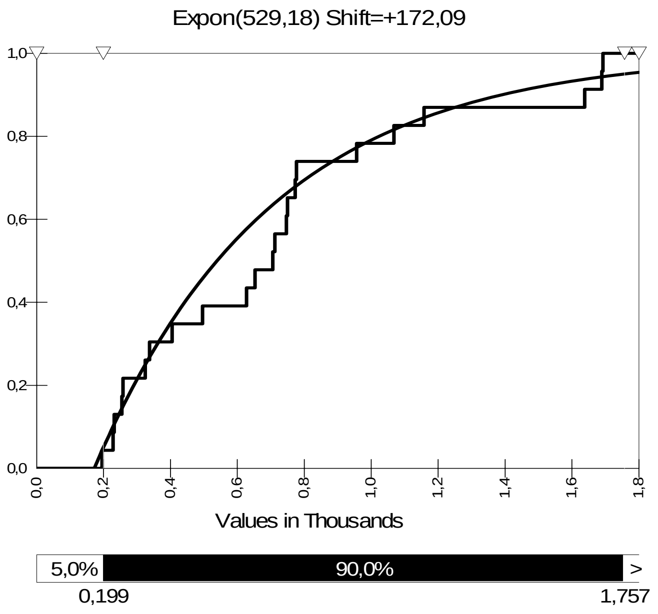

Figure 6. General Liability. Severity distribution, cost interval > 2.800 €

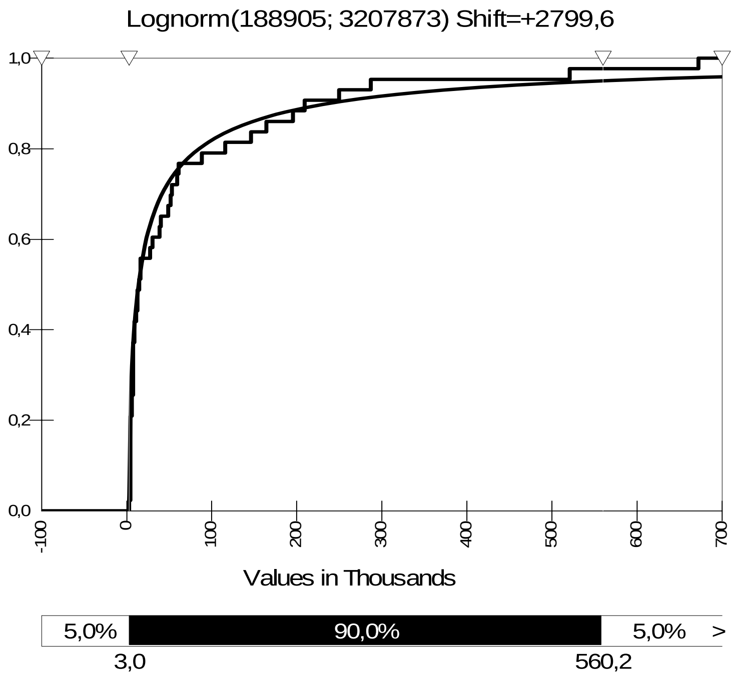

Figure 7. Property. Severity distribution, losses without coverage

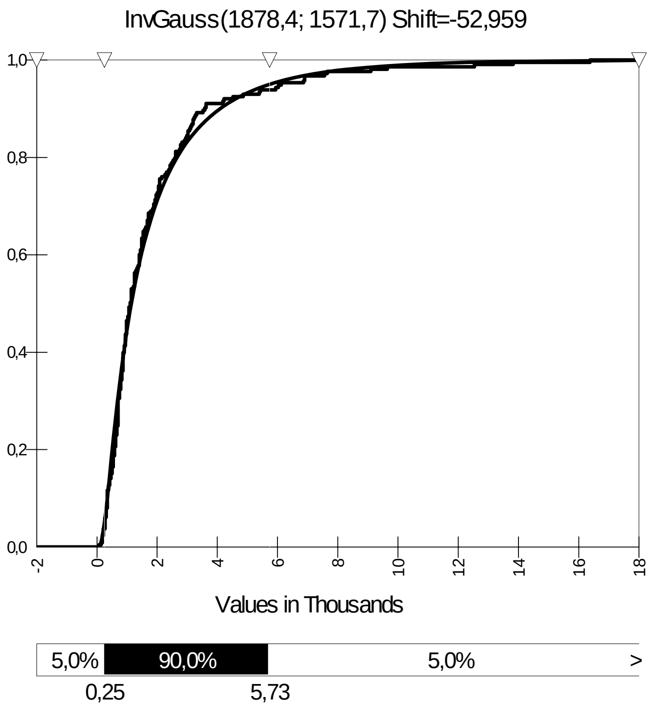

Figure 8. Health Liability. Severity distribution, losses without coverage

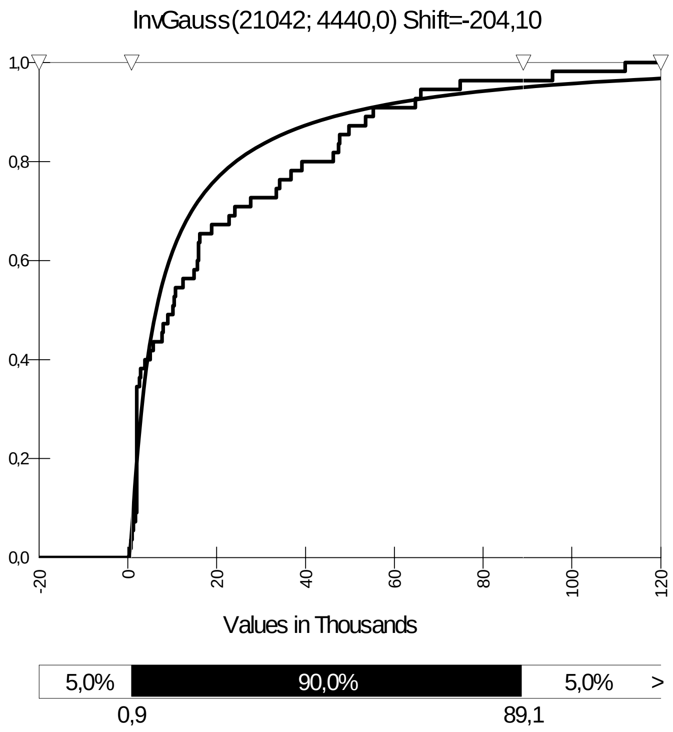

Figure 9. General Liability. Severity distribution, losses without coverage

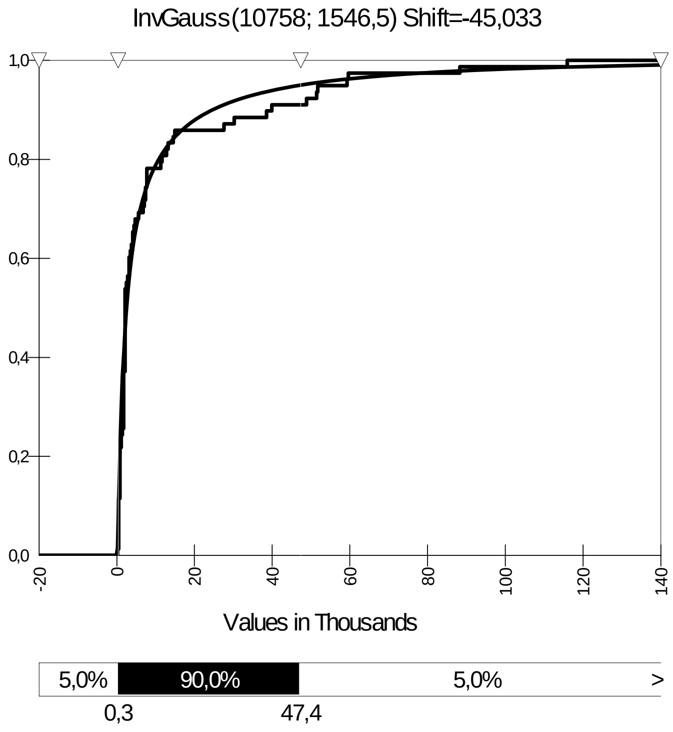

Figure 10. Property. Frequency distribution, cost interval < 350 €

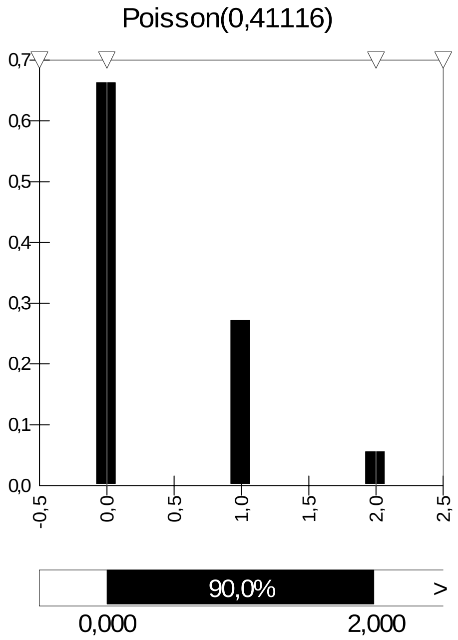

Figure 11. Property. Frequency distribution, cost interval > 350 €

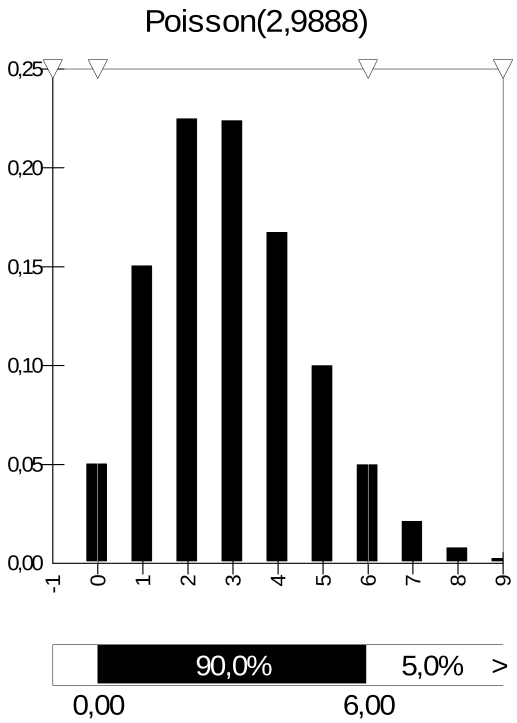

Figure 12. Health liability. Frequency distribution, cost interval < 2.000 €

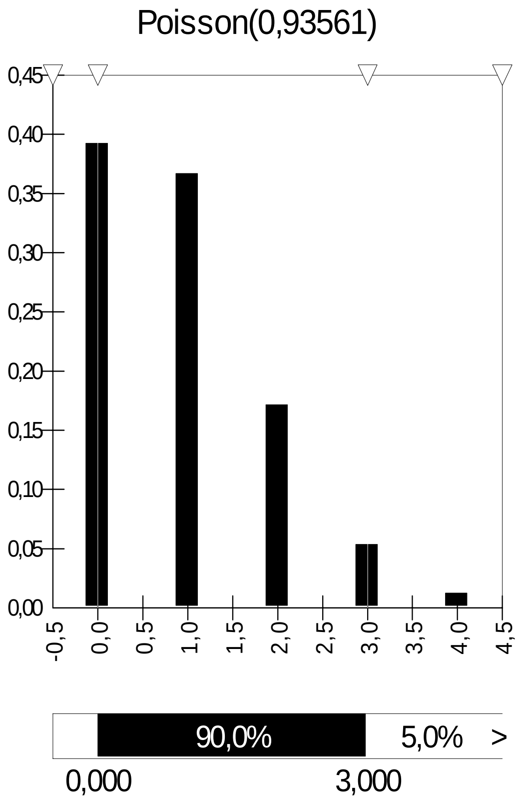

Figure 13. Health liability. Frequency distribution, cost interval > 2.000 €

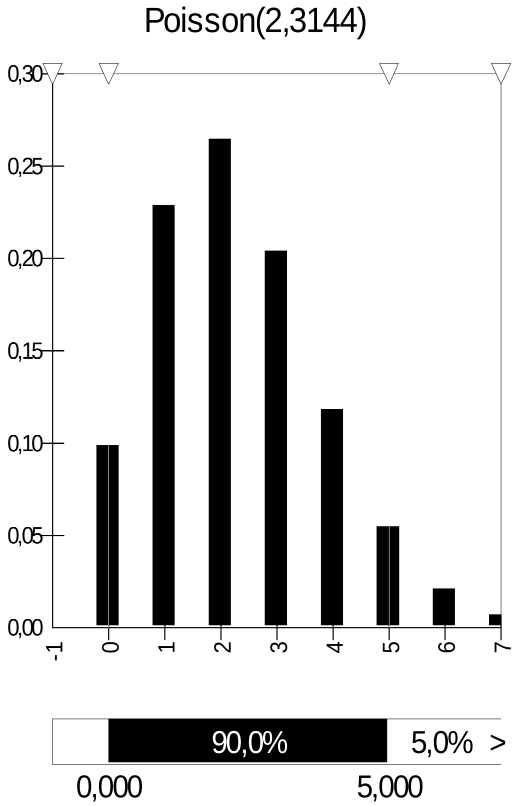

Figure 14. General Liability. Frequency distribution, cost interval < 2.800 €

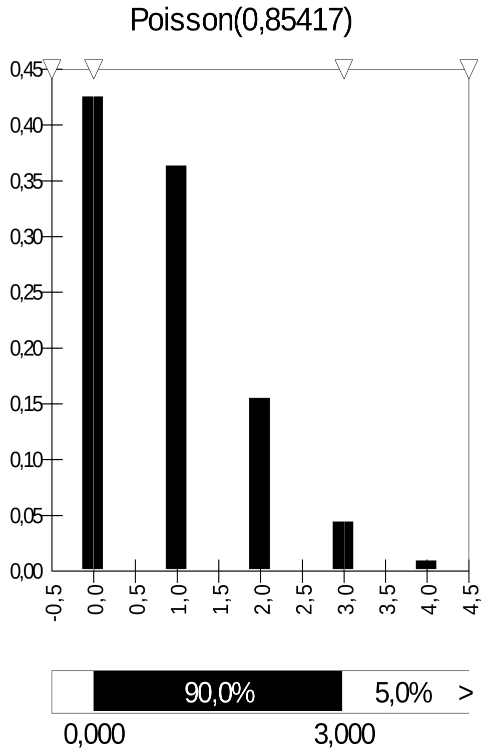

Figure 15. General Liability. Frequency distribution, cost interval > 2.800 €

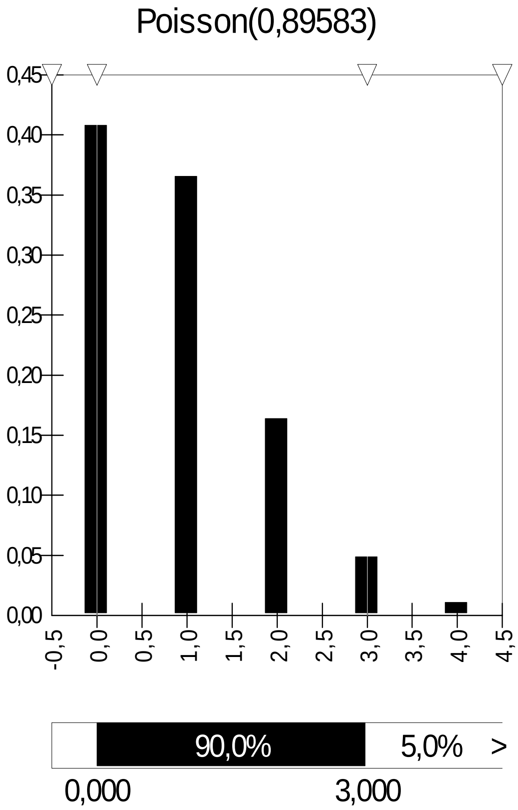

Figure 16. Aggregated loss distribution, 99.5% VaR