“Quantifying insurance risks: Monte Carlo simulations and capital requirements”

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QUANTIFYING INSURANCE RISKS: MONTE CARLO SIMULATIONS AND CAPITAL REQUIREMENTS

Abstract

The increasing complexity of insurance risks within the Solvency II regulatory framework highlights the need for accurate quantitative tools to assess the capital adequacy of insurance companies and model extreme insurance events. This study aims to demonstrate how the R programming language can be effectively used to perform Monte Carlo simulations of aggregate losses and subsequently estimate the capital requirement for large claims within partial internal solvency models used by insurance companies. The research methodology is based on Monte Carlo simulation implemented in the R programming environment using the *replicate* function to generate thousands of stochastic scenarios of claim frequency and individual claim severity based on selected probability distributions. Using real data from non-life insurance, the model generates hundreds of thousands of simulated scenarios of aggregate losses and constructs an empirical distribution of total losses from which risk measures are estimated. The simulation results show that the generated distribution captures not only the typical development of claims but also rare extreme events, which allows the estimation of the capital required to cover large claims at high confidence levels. These results enable insurance companies to more accurately quantify underwriting risk, analyze potential catastrophic loss scenarios, and determine the level of capital required to maintain solvency. The results confirm that Monte Carlo simulations implemented in the R programming language represent an effective tool for modeling aggregate losses and support risk management and capital optimization within internal solvency models.

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INTRODUCTION

The Solvency II regulatory framework represents one of the most significant pillars of modern European insurance and fundamentally influences the way insurance companies identify, measure, and manage their risks. By introducing strict capital requirements and a comprehensive supervisory system, this framework aims to strengthen the stability of the financial sector and ensure the protection of policyholders against the consequences of potential insurer insolvency. At the core of the regulatory system lies the requirement for accurate risk quantification and for determining the level of capital that an insurance company must hold to cover unexpected losses arising from its activities. Capital requirements therefore, represent a key instrument for ensuring the long-term solvency of insurance companies and their ability to meet obligations even in the event of an adverse development of claims.

However, the quantification of insurance risks is a particularly challenging task from both methodological and practical perspectives. Insurance companies face uncertainty arising from the random occurrence of insured events, the substantial variability in the severity of individual claims, and the interaction of multiple risk factors. The resulting distribution of aggregate losses often exhibits pronounced asymmetry with a long right tail, reflecting the low but economically significant probability of extreme risk events. Such rare but potentially catastrophic events may have a substantial impact on the financial stability of an insurance company and play a decisive role in determining its capital adequacy.

A particularly important problem in insurance risk management is the modeling of aggregate losses, which arise from the combination of claim frequency and individual claim severity. Accurate estimation of the aggregate loss distribution is essential for the proper determination of capital requirements, as it allows the identification of potential extreme loss scenarios. Insufficiently accurate risk quantification may lead either to an underestimation of the required capital and an increased risk of financial instability or, conversely, to excessive capital allocation, which negatively affects the operational efficiency of an insurance company. Reliable modelling of aggregate losses, therefore, represents a key prerequisite for effective insurance risk management.

In the context of modern insurance, the need to employ advanced quantitative tools that enable the realistic modelling of uncertainty and the generation of a wide range of possible loss scenarios has long been emphasized. These approaches play an important role in analyzing the risk profile of an insurance company, assessing potential extreme events, and determining the capital required to ensure solvency. Nevertheless, in practice, there still exists a methodological challenge related to the transparent and efficient modelling of aggregate loss distributions that would simultaneously allow the realistic simulation of extreme loss scenarios and provide reliable inputs for the calculation of capital requirements.

The scientific problem in this area, therefore, lies in the need to develop approaches that enable accurate modelling of aggregate loss distributions and the quantification of the capital required to cover extreme risk events while ensuring sufficient transparency and practical applicability of the models within the insurance environment.

This study aims to analyze approaches to modeling aggregate loss distributions and quantifying capital requirements for large claims in non-life insurance using a simulation approach based on Monte Carlo simulations implemented in the R programming environment.

1. THEORETICAL BASIS

The insurance industry represents a key sector of the financial market, playing an important stabilizing role in the economy by providing protection against risks arising from unforeseen events and supporting long-term financial security for households, enterprises, and public institutions (Cipra, 2015). Within this sector, non-life insurance holds a significant position, accounting for approximately 45% of total insurance premiums in the European Union in 2024, according to EIOPA data, which highlights its importance in risk transfer and reserve formation.

Given the scope of the risks undertaken and the increasing demands of regulators, the monitoring of insurers' financial stability is indispensable. In the European context, such supervision is systematically implemented in accordance with the Solvency II Directive (2009/138/EC). This regulatory framework places emphasis on adequate capital coverage, risk management, and transparency, while encouraging insurers to employ internal models capable of reflecting the specific characteristics of their portfolios (Kaas et al., 2002; Zelinová et al., 2025).

The Solvency II regulatory framework fundamentally influences how insurers identify, measure, and manage risks by introducing a comprehensive supervisory system aimed at enhancing financial stability and protecting policyholders against potential insurer insolvency. A central element of this framework is the system of capital requirements, in which the Solvency Capital Requirement (SCR)

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and the Minimum Capital Requirement (MCR) represent key regulatory tools affecting risk management and strategic decision-making of insurance companies.

To calculate the SCR, Solvency II allows two main approaches: the standard formula and internal models. The standard formula provides a unified regulatory approach suitable for insurers with a typical risk profile, ensuring comparability and simplicity. However, it may not fully reflect the specific characteristics of an individual insurer.

The calculation of the Basic Solvency Capital Requirement (BSCR) for the non-life underwriting risk module is based on the structure of the Solvency Capital Requirement (SCR) standard formula defined by the Solvency II framework (Figure 1). If the capital requirement for this module is denoted as $SCR_{non\text{-}life}$, it can be calculated as follows:

$$SCR_{non\text{-}life} = \sqrt{\sum_{i,j} corr_{ij} \cdot SCR_i \cdot SCR_j}, \qquad (1)$$

where the sum includes the SCR values for the individual risk submodules, and $corr_{ij}$ are the correlation coefficients between the SCR values for the individual non-life underwriting risk submodules, namely, premium and reserve risk, catastrophe risk, and lapse risk.

The structure of the Solvency Capital Requirement (SCR), including its main modules and submodules, is presented in Figure 1, highlighting the aggregation of individual risk components within the Solvency II framework.

The non-life catastrophe risk submodule combines capital requirements for various types of catastrophe risks, including natural catastrophes, man-made events, non-proportional reinsurance risks, and other specific non-life catastrophe risks.

The calculation of the individual SCR_i components is rather complex, as it usually combines a parametric and a scenario-based approach. In practice, the calculation of the Solvency Capital Requirement for non-life insurance ($SCR_{non\text{-}life}$) is most often carried out using partial internal models. Such a calculation of the capital requirement can be demonstrated using the collective risk model for large claims.

Non-life underwriting risk represents one of the key risks that non-life insurers take on under

Source: Solvency II Directive.

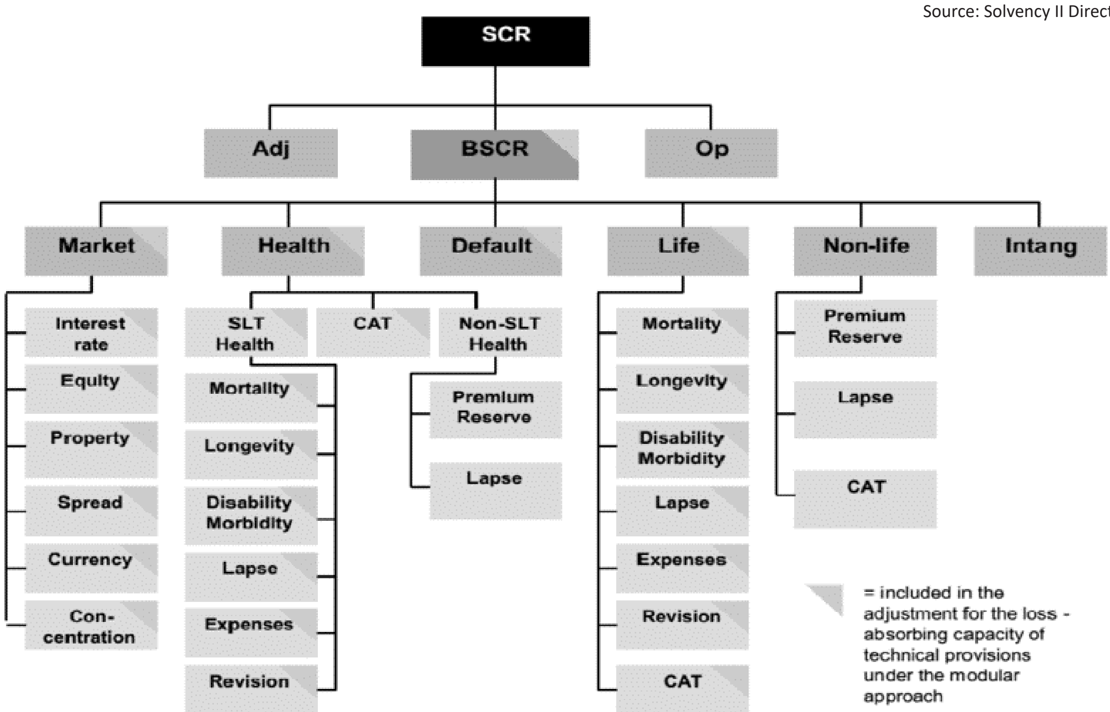

Figure 1. Standard formula Solvency II

Solvency II. It is the risk that actual claims payments, expenses, or premiums will differ from expected values, which may cause unexpected financial losses.

Internal models enable a more accurate and tailored quantification of risk, as they are designed to capture the specific structure of the insurer's portfolio. Particular attention is paid to partial internal models, which combine elements of the standard formula and internal modelling, allowing insurers to replace selected components where the standard approach does not sufficiently reflect the actual risk profile.

Internal models require a precise specification of the probability distributions of individual risks so that key indicators such as Value-at-Risk and Conditional Value-at-Risk can be correctly determined (Kaas et al., 2002; Sandström, 2011). These indicators are essential for determining economic capital and the probability of insurer insolvency (Embrechts et al., 1997), and their reliable estimation depends on an appropriate modelling of the aggregate claims distribution (Charpentier, 2014).

With the increasing complexity of insurance portfolios and the demand for more accurate risk quantification, the use of probability distributions as a fundamental tool of stochastic modelling is coming to the fore. These distributions play a key role in economics, finance, and insurance, as they allow us to describe and analyze random processes under uncertainty (Cipra, 2015; Feller, 1971). In macroeconomics, they are used to model economic cycles and shocks (Hamilton, 1989); in microeconomics to estimate the behavior of individuals and firms (McFadden, 2001); and in finance to quantify the risks of portfolios and financial derivatives (Jorion, 2007). In insurance, they form the core of actuarial calculations, as they allow the frequency of claims and the distribution of their severity to be described (Daykin et al., 1994).

A key step in the application of probability distributions is their appropriate selection and parameter estimation, i.e., distribution fitting. This process includes testing the suitability of the model on real data, comparing different types of distributions, and estimating their parameters using methods of maximum likelihood, moments, or Bayesian approaches (Klugman et al., 2012; Peters & Shevchenko, 2015). In recent years, studies have been published that focus on robust estimators for heavy-tailed distributions typical of insurance data (Fung, 2022; Poudyal & Brazauskas, 2022). Modern approaches additionally employ machine-learning methods for probability-density estimation or for modelling the risk of extreme events (Wüthrich, 2018).

In recent decades, stochastic methods have become indispensable in insurance, as they enable realistic modelling of random processes affecting insurance portfolios and support key tasks such as liability valuation, capital requirement determination, and the assessment of the probability of insurer ruin (Sandström, 2011). The increasing complexity of insurance markets, products, and regulatory requirements, particularly under Solvency II, has further strengthened the need for advanced quantitative tools capable of capturing complex dependencies among risk factors through simulation and approximation techniques (Wüthrich, 2018; Blier-Wong et al., 2021). Recent research also emphasizes the integration of stochastic models with machine-learning approaches for predicting insurance events and modelling extreme risks, as well as the use of copula models and extreme value theory within internal models (Wüthrich, 2018; Joe, 2014; Genest & Favre, 2007).

The application of probabilistic models in insurance is supported by regulatory frameworks such as Solvency II, which define capital requirements while allowing the use of internal models for the calculation of the Solvency Capital Requirement (SCR) (EIOPA, 2020).

The collective risk model (Cramér, 1930; Lundberg, 1903; Horáková et al., 2015) combines the primary distribution of the number of claims and the secondary distribution of individual claim severity into a single compound distribution. This model is the foundation of aggregate risk theory, which is used for risk measurement within one year as well as across multiple periods (Grandell, 1991). In the literature, the collective model has been analyzed in detail and extended to multiple periods, or to models with portfolio heterogeneity (Bowers et al., 1997).

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The collective risk model is a fundamental model that describes the aggregate claim amount of an insurance company over a given period of time, for example, one year. It is defined by two random components:

1. A discrete random variable N, which represents the number of claims occurring within the given period.
2. Random variables $X_1, X_2, \ldots, X_N$, which represent the individual claim severities. It is assumed that these variables are independent, identically distributed, and independent of the variable N.

The aggregate claim amount is expressed as the sum of all individual claims:

$$S = X_1 + X_2 + \ldots + X_N, \tag{2}$$

The aggregate claim amount depends on the number of claims, while the number of insurance policies and the distribution of individual claim severities remain constant throughout the observation period. It follows that the focus is on the total (aggregate) risk rather than the risk of individual insurance contracts, acknowledging that multiple claims may occur under a single policy.

A random variable that satisfies the given assumptions follows a compound probability distribution

$$S \sim Co\left(p_N(n); F_X(x)\right). \tag{3}$$

The random variable N generally follows a discrete distribution. Therefore, specific (fundamental) cases exist depending on the distribution of the number of claims N - namely, the compound Poisson distribution, the compound negative binomial distribution, and the compound binomial distribution. The random variable representing the individual claim severity may be either discrete (defined by a probability table) or continuous (described by a specific continuous probability distribution).

The distribution function of the random variable S has the following form:

$$F_S(x) = P(S \le x), \quad x \in R. \tag{4}$$

For the most important characteristics of the aggregate claim distribution of the random variable S (the expected value, variance, standard deviation, and moment-generating function), the following relations hold:

$$E(S) = E(N) \cdot E(X), \tag{5}$$

$$\begin{gathered} D(S) = E(N) \cdot D(X) + E^2(X) \cdot D(N), \\ \sigma(S) = \sqrt{D(S)}, \end{gathered} \tag{6}$$

$$m_S(z) = m_N(\ln m_X(z)). \tag{7}$$

Furthermore, it is possible to derive the distribution function $F_S(x)$, the probability function $p_S(x)$, and the moments of the aggregate claim distribution for any combination of the claim frequency distribution N and the claim severity distribution X. However, for specific choices of the claim frequency and claim severity distributions, the explicit expression of $F_S(x)$ is often very complex, particularly without the use of advanced computational techniques. The form of $F_S(x)$ for certain types of compound distributions is presented, for example, in (Horáková et al., 2015).

Knowledge of the aggregate claim distribution is indispensable for risk quantification and the calculation of capital requirements, as it enables the determination of key risk measures such as Value-at-Risk, Conditional Value-at-Risk, and the probability of ruin within a given time horizon (Artzner et al., 1999; Rockafellar & Uryasev, 2000; Asmussen & Albrecher, 2010). These measures play a crucial role in assessing the insurer's financial stability and in determining economic capital, which is fundamental within regulatory frameworks such as Solvency II (Sandström, 2011).

Value-at-Risk (VaR) represents the maximum loss that may occur with a specific probability over a given period. For the random variable S describing the loss occurring with probability p, $VaR_p(S)$ is the 100 p % quantile, $0 < p < 1$, for which the following holds:

$$VaR_p(S) = \inf\{x \in R : F_S(x) \ge p\}. \tag{8}$$

Conditional Value-at-Risk (CVaR) represents the expected loss from all losses exceeding the quantile value x_p of the corresponding distribution. In the case of a continuous distribution of the random variable S, it takes the form:

$$CVaR_p\left(S\right)=\frac{\int_{x_p}^{\infty} x\cdot f_S\left(x\right)dx}{P\left(S>x_p\right)}. \tag{9}$$

In the discrete case of the random variable S, the value of $CVaR$ is expressed as:

$$CVaR_p\left(S\right)=\frac{\sum_{S>x_p} x\cdot p_S\left(x\right)}{P\left(S>x_p\right)}. \tag{10}$$

Probability of ruin expresses the probability that the insurer's surplus falls below zero at the end of the observation period. The insurer's surplus during a single time period is defined by the random variable ($U_1 = U + RP - S$), where: U – denotes the initial reserves at the beginning of the observation period; RP – is the total risk premium received for one time period, calculated according to the expected-value principle in the form $RP = (1 + \sigma) \cdot E(S)$, S – represents the aggregate claim for one time period.

The objective of the insurance company is to ensure that the surplus at time $t = 1$, i.e., at the end of the time period, remains positive, or equivalently, that the following holds with a very small probability:

$$P\left(U+RP-S<0\right)=\varepsilon. \tag{11}$$

Which, after rearrangement, can be expressed in the form:

$$P\left(S<U+RP\right)=1-\varepsilon, \tag{12}$$

or, equivalently:

$$F_S\left(U+RP\right)=1-\varepsilon. \tag{13}$$

The distribution of the total (aggregate) claim can be determined using several approaches. Analytical methods, such as convolution sums or Panjer's recursion, provide accurate results for specific types of insurance models (Panjer, 1981) but may become computationally demanding or infeasible in more complex settings, for example, when claims are correlated or distributions are mixed (Charpentier, 2014; Sundt & Jewell, 1981). Alternative approaches include approximation methods, such as normal-power or shifted-gamma approximations, which often yield lower accuracy (Dhaene & Sundt, 1997). For this reason, simulation methods are frequently preferred in practice, as they allow for flexible modelling of aggregate losses and enable the numerical approximation of the aggregate claims distribution based on the assumed distributions of claim frequency and severity (Rubinstein & Kroese, 2016).

The following approaches are commonly used:

- numerical methods (convolution sums);
- recursive procedures (Panjer's recursive relations);
- approximation methods (e.g., approximation by the normal or shifted gamma distribution);
- simulation methods (primarily Monte Carlo simulations).

Monte Carlo simulations represent a flexible and widely used method for approximating the distribution of aggregate claims in situations where analytical or approximation methods are infeasible (Rubinstein & Kroese, 2016; Glasserman, 2004). Originally developed for computational problems in physics (Metropolis & Ulam, 1949), this technique has found broad application in finance, insurance, and risk management (Boyle, 1977; Embrechts et al., 1997; Simonka, 2025). In the context of insurance, Monte Carlo simulations play a key role in modeling aggregate risk, estimating the probability of ruin, and determining capital requirements. Their importance is particularly evident in internal and partial internal models, where they enable the simulation of complex risk structures, including claim frequency and severity, reserve development, and catastrophic risks modelled via frequency–severity approaches or extreme value theory. By generating a large number of stochastic scenarios, Monte Carlo simulations provide realistic approximations of loss distributions and allow for the accurate estimation of key risk measures, such as Value-at-Risk and Conditional Value-at-Risk, even in cases where

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the exact distribution of aggregate losses cannot be derived analytically.

Since the exact form of the aggregate loss distribution is often difficult to obtain, Monte Carlo simulations are used to generate values of the random variable S and compute the corresponding risk measures.

With the increasing computational complexity of insurance models, information technologies play a crucial role in their practical implementation. In actuarial practice, the R programming language has proven to be an efficient and flexible tool for simulation-based calculations, enabling the generation of random variables, computation of risk measures, and visualization of results (Charpentier, 2014; Páleš, 2019). In the context of Monte Carlo simulations, the real system is replaced by a stochastic simulation model with identical probabilistic characteristics, and repeated simulations provide accurate estimates of risk measures even for complex compound distributions.

Open-source environments such as R and Python offer extensive libraries for these purposes; in R, widely used packages include *actuar*, *fitdistrplus*, *copula*, and *RiskSimul* (Charpentier, 2014; Dutang et al., 2008), while Python relies on libraries such as *numpy*, *scipy*, and *pandas*. The R environment is particularly suitable for actuarial applications due to its specialisation in insurance modelling and openness to further development (Dutang et al., 2008).

An important practical aspect is the use of the *replicate* function, which enables the efficient generation of a large number of simulation runs and represents a simple yet powerful tool for implementing Monte Carlo simulations in actuarial applications, as first presented by Driscoll and Murphy (2009) in *An Interactive Introduction to R for Actuaries*, CAS Conference in Boston. By generating simulated values of aggregate losses, this approach enables the direct estimation of key risk measures such as Value-at-Risk, Conditional Value-at-Risk, and the probability of ruin, which are essential for assessing financial stability and determining capital requirements in insurance. Despite the broad literature on Monte Carlo methods, relatively little attention has been devoted to this specific implementation approach in the context of aggregate loss modelling, which motivates its application in this study.

2. RESULTS AND DISCUSSION

2.1. Author´s methodology

The analysis focuses on modelling non-life underwriting risk within a partial internal model framework, capturing key sources of uncertainty relevant for capital determination.

The simulation model for estimating capital requirements for large losses within a partial internal model is presented using real parameters derived from insurance practice. The CVaR risk measure was applied to determine the capital requirement.

The non-life underwriting risk model, therefore, serves to quantify this uncertainty and to determine the capital needed to cover extreme but realistic deviations from planned outcomes. Based on the Solvency II Directive, the model generally includes three main risk components:

1. Premium risk – the risk associated with future insurance claims that will arise from the current insurance portfolio during the following year.

2. Reserve risk – the risk that existing technical provisions will prove to be insufficient in light of the actual development of claims.

3. Catastrophe (CAT) risk – the risk of the occurrence of catastrophic events, such as floods, earthquakes, windstorms, or industrial disasters.

The non-life underwriting risk model works with projected claims flows, volatility parameters, correlations, and, where relevant, specific distributions for individual insurance segments. The model aims to capture not only average expected values, but especially variability, extreme events, and estimation uncertainty.

In practice, the partial internal model consists of several components, as illustrated in Table 1,

Table 1. Non-life underwriting risk model

Source: Author's own processing (based on information from insurance practice).

Non-life underwriting risk model		Aggregation model
GROSS MODEL	*RESERVE MODEL*	Economic underwriting results Risk Capital Other KPI's
Gross written premium Costs Portfolio development Losses (attritional, large, CAT)	*REINSURANCE MODEL* *C-F MODEL*	

Table 2. Generation of aggregate claim values in R for various combinations of random variables N (claim count) and X (claim severity) distributions

Source: Author's own processing, based on Páleš (2019).

N	X	R code

Discrete *(table)*	***Discrete*** *(table)*	`n<-c(0,1,2); pn<-c(0.81,0.18,0.01)`
		`x<-c(0,1,2); px<-c(0.7,0.1,0.2)`
		`S<-replicate(500000,sum(sample(x,`
		`sample(n,1,prob=pn,repl=T),prob=px,repl=T)))`

Discrete *(distribution)*	***Discrete*** *(table)*	`x<-c(0,1,2); px<-c(0.7,0.1,0.2)`
		`size<-2; prob<-0.1`
		`S<-replicate(500000,sum(sample(x,`
		`rbinom(1,size,prob),prob=px,repl=T)))`

Discrete *(distribution)*	***Discrete*** *(distribution)*	`lambda1<-3; lambda2<-1` `S<-replicate(500000, sum(rpois(rpois(1,lambda1),lambda2)))`

Discrete *(table)*	***Continuous*** (distribution)	`n<-c(0,1,2); pn<-c(0.81,0.18,0.01)`
		`rate<-0.1`
		`S<-replicate(500000, sum(rexp(sample(n,1,prob=pn,repl=T),`
		`rate)))`

Discrete *(distribution)*	***Continuous*** *(distribution)*	`lambda<-30`
		`rate<-0.1`
		`S<-replicate(500000, sum(rexp(rpois(1,lambda),rate)))`

where this paper focuses on large losses. For instance, copula functions are commonly employed to aggregate individual risks.

The objective is to generate values of a compound distribution using the Monte Carlo simulation method, based on the assumed knowledge of the claim frequency distribution and the claim severity distribution. The values of the aggregate claim thus generated are subsequently used to calculate the required risk measures, such as Value-at-Risk, Conditional Value-at-Risk, and the economic capital. The simulation is carried out using the R programming language and its built-in function *replicate*, which enables the efficient generation of a large number of simulations.

Table 2 summarizes selected examples of such combinations together with sample R code that enables the generation of simulated aggregate claim values S. The obtained sample then serves as a basis for calculating risk measures such as Value-at-Risk, Conditional Value-at-Risk, economic capital, probability of ruin of the insurance company, etc. These simulation procedures form the basis for the practical application presented in the following subsection.

2.2. Practical application and results

Monte Carlo simulations enable the generation of aggregate loss values (compound distribution) in situations where analytical solutions are unavailable or computationally demanding, particularly in models with heavy-tailed or complex distributions. Unlike analytical approaches such as convolution methods or Panjer recursion, which are often limited to specific distributional assumptions, Monte Carlo simulations enable the direct generation of aggregate loss values based on the assumed distributions of claim frequency and severity. This simulation-based approach makes it possible to approximate the distribution of total losses even in complex settings, where traditional methods fail or become numerically unstable.

As the number of simulations increases, the simulated results converge towards the theoretical val-

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ues, and with a sufficiently large number of iterations (e.g., 500,000), the differences become negligible. This confirms the accuracy and reliability of the Monte Carlo approach for modelling aggregate losses and estimating corresponding risk measures.

For capital requirements and calculation of ruin probability, the following code can be used:

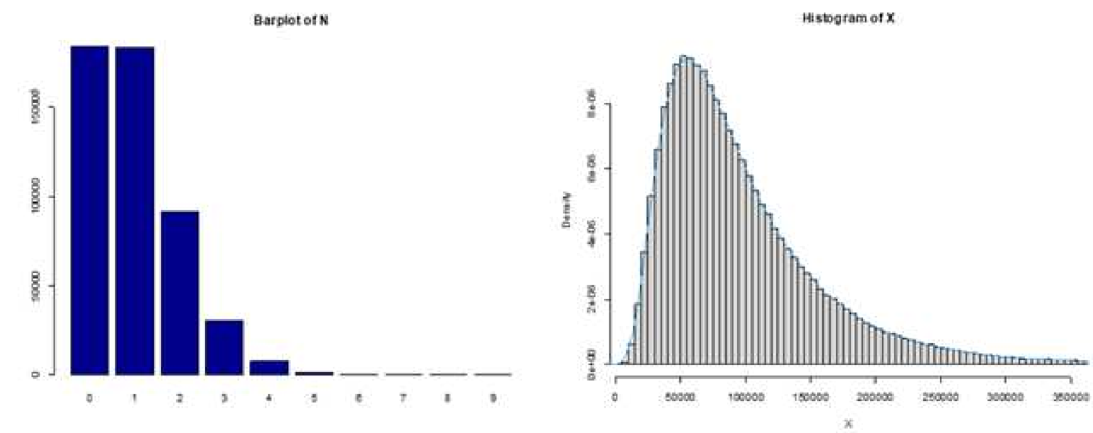
```
n_simul<- 500000
S <- replicate(n_simul,sum(rlnorm(rpois
(1,lambda),mu,sigma)))
VaR <- quantile(S,p)
CVaR <- mean(subset(S,S>VaR))
U <- 0 #example
RP <- (1+delta)*mean(S)
P <- 1-length(subset(S,S<U+RP))/length(S)
```

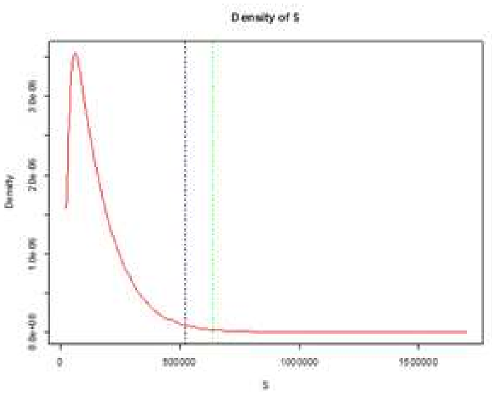
Assuming that the characteristics of the claim count distribution are known, which can be estimated from the insurer's real data (the company name is not disclosed for data protection reasons), and that $E(N) \cong 1$ and $D(N) \cong 1$, then, since $E(N) \sim D(N)$, it may be assumed that the number of claims follows a Poisson distribution with parameter $\lambda = 1$. The individual claim severity follows a lognormal distribution with parameters $MW = 100{,}000$ and $StdDev = 70{,}000$, from which $\mu = 11.31354$ and $\sigma = 0.63149$. This assumption can be verified using the Kolmogorov–Smirnov goodness-of-fit test, or alternatively, by a Q–Q plot.

Let us carry out 500,000 Monte Carlo simulations with the given parameters and determine the capital requirements $VaR_{0.99}(S)$ and $CVaR_{0.99}(S)$, which are indicated on the plot of the density of the aggregate-claim distribution (Figure 2, bottom-left). The computation was performed using the algorithm described in Table 2.

Assuming that the partial capital requirement for large claims corresponds to the Conditional Value-at-Risk (CVaR), it can be estimated at ≈ 638,488.6 monetary units. The (basic) economic capital for such large claims is therefore ≈ 538,497.8. The difference in the amount of economic capital calculated using VaR and $CVaR$ is ≈ 115,366.1.

Source: Author's own processing.





Characteristic	Value
E(S)	99,990.82
D(S)	14,942,400,000
VaR0.99	523,122.40
CVaR0.99	638,488.60

Figure 2. Partial internal model for large claims using Monte Carlo simulations

An important advantage of the Monte Carlo simulation approach is that it generates values of the random variable *S* that can subsequently be used in further analyses, for example, within ruin theory, reinsurance modelling, or other insurance applications.

In this study, the analysis focused on data on the number of insurance claims and the individual claim size within the insurance portfolio of large losses, using Monte Carlo simulations to generate realistic scenarios of claim development. This approach enabled the generation of values for the aggregate loss distribution, which were subsequently used to calculate relevant risk measures and, thereafter, economic capital. These methods provide a clear and robust framework for quantifying potential losses in the event of extreme events and allow for a better understanding of the level of capital reserves needed to cover these risks.

The results of simulations show that CVaR is a particularly valuable tool in risk assessment, because it considers not only the probability that losses will exceed a certain threshold, but also their average impact in the case of extreme events. This approach proves to be more accurate and more robust than traditional VaR, which does not take into consideration the magnitude of losses in unlikely but potentially catastrophic events. The calculation of economic capital, which serves as the capital ensuring solvency, is performed on the basis of CVaR, thereby ensuring that the insurer will be able to withstand even very severe and unlikely risks that could seriously threaten its financial stability.

The analysis also shows that the economic capital calculated using this method can be considered analogous to the solvency capital that is calculated in the standard formula under the Solvency II regulation. Although the standard formula provides conservative and standardized estimates of capital requirements, internal models based on simulations, such as Monte Carlo, allow insurers to tailor their capital reserves more closely to their specific risk profile. In this way, insurers can protect themselves more effectively against risks that are unique to their portfolios, while at the same time complying with regulatory solvency requirements. This approach proves to be a powerful tool for insurers that strive for more accurate and flexible management of capital reserves.

When connecting the results of the simulations with the theory of ruin probability, a significant benefit can be observed in the quantification of the risk that may threaten the financial stability of an insurer. Ruin Theory deals with the analysis of the probability that an insurer or any financial institution will fall into ruin or insolvency as a result of continuous losses that exceed its available capital reserves.

While CVaR provides a value that represents the average losses for a given probability of exceeding a certain threshold (e.g., 99%), the probability of ruin enables us to determine the likelihood that an insurer will be unable to cover its liabilities as a result of unforeseen and large losses arising from claim events.

The relationship between the economic capital determined using CVaR and the probability of ruin can be made by focusing on the likelihood that the total amount of loss, as simulated by Monte Carlo methods, exceeds the insurer's available capital. If the simulated losses in selected scenarios exceed the capital reserve, this shortfall can be considered a "ruin" scenario, in which the insurer would not be able to cover all its obligations towards its clients.

In practice, Monte Carlo simulations can be used to estimate the probability that the amount of loss arising from a given risk will exceed the insurer's capital reserves. This provides the probability of ruin depending on the level of capital reserves. For example, if the probability of exceeding the capital reserve is too high (e.g., higher than the established regulatory threshold), this may indicate the need to increase the insurer's capital reserve to reduce the probability of insolvency.

This approach enables insurers not only to quantify risk effectively in terms of capital requirements, but also to assess financial stability through the probability of ruin. Within the Solvency II framework, such a relation is crucial, because insurers must ensure sufficient capital to cover risks that could threaten their ability to meet obligations towards clients even in the case of very adverse scenarios. In this sense, the analysis of Monte Carlo simulations in the context of Ruin Theory is an invaluable tool for optimizing capital reserves and ensuring the insurer's solvency over the long term.

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CONCLUSION

The aim of this study was to analyze the use of Monte Carlo simulations in determining capital requirements for solvency, with a focus on non-life insurance and implementation in the R programming environment. The results showed that internal and partial internal models help insurers more accurately assess risks associated with the frequency and severity of insurance claims, while Monte Carlo simulations generate realistic distributions of aggregate losses and enable the calculation of risk measures such as Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). The *replicate* function proved to be a flexible and efficient tool that allows a large number of simulations to be performed in a single step, ensures a consistent structure of outputs, and increases code transparency. This approach minimizes the risk of errors, simplifies the testing of alternative parameters and distributions, and supports the validation of internal models and the implemented software solution by regulatory supervisory authorities.

The obtained results further show that the methodology based on the replicate function provides a robust framework for analyzing the risk profile of an insurance company, enabling more detailed quantification of capital reserves and supporting effective financial resource management even in the presence of extreme events. This approach makes it possible to simulate not only traditional scenarios with a discrete number of claims and continuous claim severity, but also more complex combinations that may better reflect the specific characteristics of a particular insurer. At the same time, it allows the implementation of stress testing, the estimation of ruin probabilities, and the optimization of capital structure under reinsurance arrangements, thereby contributing to the enhancement of insurers' stability and financial security. Overall, this methodology contributes not only to more accurate risk management but also to a more effective use of available analytical tools and libraries in the R environment. The methodology presented thus represents a significant contribution for actuaries and risk management professionals, who can apply simulation techniques more accurately and directly within their internal models.

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