



Analysis of Ruin Probability in Insurance Companies Using the Cramer-Lundberg Model with Variations in Claim Distributions

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ABSTRACT

Ruin risk is a critical concern in the insurance industry, reflecting a company's ability to fulfill long-term claim obligations. This study estimates ruin probabilities using the Cramer-Lundberg model, with Monte Carlo simulation applied to three claim distributions: exponential, lognormal, and gamma. Simulations vary initial capital while holding the premium rate, claim intensity, and distribution parameters constant. Results show that the lognormal distribution, due to its heavy tail, leads to higher ruin probabilities compared to exponential and gamma distributions. The gamma distributions produce intermediate outcomes, while the exponential shows the lowest risk. These findings highlight the importance of considering distributional characteristics when assessing solvency risk. The study provides practical insights for actuaries and risk managers in evaluating capital adequacy, stress-testing portfolios, and developing adaptive pricing and reinsurance strategies.

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1. INTRODUCTION

Financial risk arising from certain events is often anticipated by individuals through the use of insurance services. In the industrial context, the insurance sector plays a significant role in the economy as an institution that manages and transfers risk from individuals or groups to a company [1],[2]. Insurance companies operate by collecting premiums in exchange for coverage guarantees and in return, are obligated to pay claims when insured risks materialize. However, variability in claim sizes and uncertainty in the frequency of events make insurance companies vulnerable to ruin risk. Ruin occurs when a company's reserve funds can no longer cover the total amount of incoming claims. This situation may result from several factors, including high aggregate claims within

a specific period, premiums that are not commensurate with the level of risk, and an imbalance between premium income and claim liabilities.[3]

The classical Cramer-Lundberg risk model is one of the most widely used approaches in actuarial risk theory to quantitatively understand and measure ruin risk [4]. This model simplifies the surplus dynamics of an insurance company as a stochastic process consisting of continuous premium inflow and randomly occurring claims in both magnitude and timing [5]. Based on this model, the ruin probability can be calculated as a function of parameters such as claim arrival intensity λ , claim size distribution, premium rate, and initial capital [6]. However, fluctuating market conditions and non-ideal claim patterns in practice often make the analytical approach of the Cramer-Lundberg model less representative. Therefore, numerical methods such as Monte Carlo simulation are needed. One of the main limitations of the Cramer-Lundberg model lies in its assumption of simple claim distributions, such as the exponential distribution, which rarely reflects the actual characteristics of claim data that are often right-skewed or heavy-tailed [8].

Additionally, the analytical approach becomes increasingly inadequate when premium structures are dynamic, deductibles are applied, or complex reinsurance strategies are implemented [9]. Volatile market conditions and non-stationary claim patterns make closed-form solutions of traditional models less accurate in capturing ruin risk. In response, Monte Carlo simulation offers a numerical approach capable of handling complexities that analytical methods cannot [7]. This method allows for the random replication of various surplus scenarios based on more realistic parameters and distributions. It not only accommodates heavy-tailed claim distributions like the lognormal, but also flexibly simulates complex premium structures and risk management strategies, including reinsurance.

Furthermore, Monte Carlo simulation enables empirical estimation of ruin probability by calculating the proportion of scenarios in which the surplus falls below zero over a specific time horizon. This yields more accurate estimations under real-world conditions than conventional approaches. Additionally, this method enables sensitivity analysis to parameter changes such as claim intensity, claim size, and premium rate, making it a vital tool in risk management practices, minimum capital estimation, and adaptive premium strategy development in response to extreme risks [12]. With its flexibility and higher estimation accuracy, Monte Carlo simulation not only addresses the limitations of the Cramer-Lundberg model but also serves as a key decision-making tool in modern risk-based insurance industry management [5].

In practical terms, the Cramer-Lundberg model and Monte Carlo simulation are widely applied in insurance company operations for tasks such as capital adequacy assessment, premium rate determination, and reinsurance planning. Actuaries use these models to perform solvency stress tests, ensuring that the company can withstand extreme claim events while maintaining regulatory compliance. By simulating various claim scenarios and market conditions, insurers can identify the probability of financial distress and adjust their underwriting policies, safety loading coefficients, and investment strategies accordingly.

Moreover, these models support decision-making in day-to-day operations by providing quantitative measures for setting premium levels, optimizing reserve allocation, and evaluating the risk-return profile of different insurance portfolios. This enables insurance companies to proactively manage insolvency risk, enhance financial stability, and protect policyholders' interests in both stable and volatile economic environments. Therefore, this study focuses solely on analysing the ruin probability of insurance companies using the Cramer-Lundberg model enhanced with Monte Carlo simulation.

Three claim size distributions exponential, lognormal, and gamma are selected to reflect the variety of claim patterns observed in insurance practice. The exponential distribution is the most classical in risk theory due to its memoryless property and analytical tractability, making it suitable for illustrating the analytical Cramer-Lundberg model [3]. The lognormal distribution, characterized by heavy tailed behaviour, captures the possibility of rare but financially significant large claims [1][4]. The gamma distribution offers high flexibility in modelling claim sizes through its two parameters, which control scale and shape, making it suitable for claims with moderate to high variance and often serving as an empirical alternative to the lognormal distribution [9].

By comparing these three distributions, the study aims to analyse the sensitivity of ruin probability to claim size distributional forms and to evaluate the extent to which insolvency risk increases when more realistic models are applied. This research contributes to the actuarial risk theory literature by addressing two existing works on the Cramer-Lundberg model remains focused on analytical solutions using the exponential distribution, while mathematically elegant, fails to capture the diversity of real-world claim distributions [3]. Empirical distributions such as lognormal and gamma, which align more closely with observed insurance data, have not been systematically analysed in the context of numerical simulation. Second, studies integrating Monte Carlo simulation to evaluate ruin probability under non-exponential claim distributions remain scarce, particularly in terms of cross distribution comparisons and sensitivity analyses involving actuarial parameters such as claim intensity, initial capital, and premium loading [1][8].

By adopting a Monte Carlo based numerical approach and explicitly comparing three claim size distributions, this study enhances the understanding of insurers' financial resilience. Beyond theoretical contributions, the findings offer practical implications for insurers in conducting portfolio stress-testing, estimating minimum capital

requirements, and designing premium and reinsurance strategies that are more adaptive to extreme risk management practices in both national and global insurance industries.

2. RESEARCH METHOD

This study is quantitative research employing a computational simulation approach. The main objective is to evaluate the ruin probability of an insurance company using the Cramer-Lundberg model, and to compare the outcomes when claim distributions are modeled using exponential, lognormal, and gamma distributions.

The steps in this research are as follows:

Formulation of the Cramer-Lundberg Model

The base model used is:

$$R(t) = u + c(t) - \sum_{i=1}^{N(t)} X_i, t \geq 0 \quad (1)$$

where,

$R(t)$ = Insurer's surplus at time t ,

u = Initial capital at $t = 0$,

$c(t)$ = Constant premium income rate per unit time,

$N(t)$ = Number of claims up to time t , modelled as a homogeneous poisson process with intensity $\lambda > 0$,

X_i = Size of the- i claim, assumed i.i.d random variables from a specified claim size distribution (e.g., exponential, lognormal, gamma).

The model assumes that premiums are collected continuously at a constant rate, while claims occur randomly over time according to a poisson process. The independence between $N(t)$ and X_i is a standard assumption in classical risk theory, allowing analytical tractability. However, in real-world scenarios, claim amounts and arrival times may be dependent, motivating the use of simulation-based methods for more accurate estimation.

Claim Distribution Modeling

The simulations are conducted using three types of claim distributions. The exponential distribution (β) is employed to represent light tailed claims with relatively small average values. The lognormal distribution (μ, σ^2) is applied to capture large claims with heavy tailed characteristics. Meanwhile, the gamma distribution (α, θ) is chosen for its flexibility in distribution shapes, allowing it to accommodate various patterns of claim data that may arise.

Premium Determination

Premium's determination refers to the rate at which premium income is collected per unit of time. If the premium rate exceeds the expected aggregate claims, the insurer's surplus is expected to grow over time. However, when premiums are not appropriately aligned with underlying risk (a condition known as underpricing), the probability of ruin increases substantially [2][8]. In this study, the premium rate is determined using the loaded premium principle, which introduces a safety margin to account for uncertainty and potential adverse deviations in claim experience. Mathematically, the premium rate c is defined as [3][4]:

$$c(t) = (1 + \theta)\lambda E(X) \quad (2)$$

where,

λ is the claim arrival intensity (expected number of claims per unit time)

$E(X)$ is the expected claim size, and

$\theta > 0$ is the safety loading coefficient.

Monte Carlo Simulation

In various studies implementing Monte Carlo simulation for actuarial risk modelling, the selection of the number of iterations plays a crucial role in ensuring the accuracy of the estimation. The selections of 10.000 iterations in the Monte Carlo simulations employed in this study was not determined arbitrarily, but rather based on a consideration of the balance between estimation stability and computational efficiency. Several studies in the literature indicate that, in the context of estimating ruin probability, an iteration count in the range of 10.000 to 100.000 is generally sufficient to produce convergent estimates with a small standard error [8]. The selection of 10.000 iterations in this study balances the need for estimation stability with computational efficiency. To illustrate this trade-off, additional simulations were performed with 5.000 and 10.000 iterations under identical parameter

settings. Table 1 presents the estimated ruin probabilities and standard errors for these iteration counts. The results indicate that while the estimates converge as the number of iterations increases, the improvement in accuracy beyond 10,000 iterations is marginal relative to the additional computational cost.

Table 1. Effect of Iteration Count on Estimated Ruin Probability

Iterations	Estimated Ruin Probability	Standard Error
5.000	0.2141	0.0058
10.000	0.2134	0.0041
100.000	0.2137	0.0013

This comparison confirms that 10,000 iterations provide a sufficiently accurate estimate (standard error < 0.005) while keeping computational time manageable. Larger iteration counts yield only marginal improvements in precision, making 10,000 an optimal choice for the present study. A sufficiently large number of iterations is required to ensure that the simulation results converge toward the true expected value. The chosen iteration count provides an optimal balance between numerical precision and the computational resources utilized. Accordingly, 10,000 iterations were selected as the optimal value large enough to ensure estimation accuracy with a narrow confidence interval, yet efficient in terms of resource usage. This strategy is also consistent with common practices in risk simulation within the insurance industry [12]. Therefore, in this study, 10,000 iterations were employed as the basis for estimating the ruin probability under the Cramer-Lundberg model, with the simulation conducted accordingly to obtain the estimated ruin probability [9],

$$\psi(u) = \frac{\text{Number of simulations with } R(t) < 0}{\text{Total simulations}} \quad (3)$$

Ruin Probability Calculation

Ruin probability is one of the key risk measures in actuarial science. In the Cramer-Lundberg model, it is defined as:

$$\psi(u) = P(U(t) < 0 \text{ for some } t \geq 0 | U(0) = u) \quad (4)$$

This probability depends on various factors including initial capital, premium rate, claim intensity, and the claim size distribution. In some simple cases, such as exponentially distributed claims, analytical solution for $\psi(u)$ exist. However, for more complex distributions, numerical methods or simulations are more commonly used [3].

Sensitivity Analysis

Sensitivity analysis is a method used to evaluate how changes in model inputs or parameters affect the outcomes of the model. In the context of the Cramer-Lundberg model, which is employed to estimate the ruin probability of an insurance company, sensitivity analysis is crucial as it enables researchers or practitioners to identify which factors have the greatest impact on insolvency risk [3]. This understanding supports strategic decision-making, including premium setting, capital reserve determination, and reinsurance policy development [1]. Below are key interrelated variables in the model and their relationship with ruin probability. In the Cramer-Lundberg model, several key parameters determine the dynamics of an insurer's surplus process. The initial capital (u) refers to the reserve funds held by the insurance company at time $t = 0$. A higher lever of initial capital reduces the probability of ruin since it provides a larger buffer against potential claim losses [3]. Another crucial factor is the claim arrival intensity (λ), which represents the average number of claims arriving per unit of time. An increase in λ indicates more frequent claims, which may deplete the reserve more quickly and raise the likelihood of the surplus turning negative [4]. Equally important are the claim size distribution parameters, which describe how claim amounts are spread. For example, the exponential distribution typically models frequent small claims, whereas lognormal or gamma distributions are employed to capture the possibility of large, infrequent, heavy-tailed claims. A more dispersed distribution with higher variance increases the risk of extreme losses that can significantly erode reserves [7]. Finally, the safety loading coefficient (θ) serves as an adjustment factor in actuarial risk theory. It is applied to premiums to ensure that they exceed the expected value of claims, thereby creating a margin to account for uncertainty and variability. This margin helps insurers remain solvent in the face of large claims or unexpectedly high claim frequencies. In the Cramer-Lundberg framework, θ is generally set to a positive value, reflecting the company's risk management strategies, regulatory constraints, and tolerance toward claim fluctuations [2].

2.1 Classical Risk Theory

Classical risk theory forms the fundamental basis of actuarial science in modelling the surplus of insurance companies. This mode treats the company's cash flow as a stochastic process, under the following assumptions.

Premiums are assumed to be received continuously at a constant rate, while claims arrive randomly according to a Poisson process. Furthermore, claim sizes are modeled using a specified probability distribution, such as the Exponential, Gamma, or Lognormal distribution. This model was first developed by Filip Lundberg (1903) and later refined by Harald Cramer, and is thus widely known as the Cramer-Lundberg model. It is used to analysis the ruin probability, which is the likelihood that the insurer's surplus becomes negative within a certain time horizon [5].

2.2 Claim Size Distributions

The choice of claims size distribution plays a critical role in risk modelling, as it directly influences the accuracy of ruin probability estimation. Several distributions are commonly applied in actuarial practice. The Exponential distribution is often used due to its mathematical convenience and memoryless property, making it suitable for modeling small and frequent claims [7]. In contrast, the Lognormal distribution is more appropriate for claim data characterized by high skewness or heavy tails, capturing the possibility of large, infrequent claims [5]. The Gamma distribution, on the other hand, provides greater flexibility for modeling claims with moderate variance, offering a balance between light-tailed and heavy-tailed behaviors [4]. The selection of the appropriate distribution is therefore essential, as it ensures that the model reflects realistic claim patterns and produces reliable estimates of ruin probability.

2.3 Monte Carlo Simulation

Monte Carlo simulation is a powerful numerical method used for modelling complex stochastic systems, including those in insurance. In the context of the Cramer-Lundberg risk model, it is used to empirically estimate the ruin probability, particularly when analytical solutions are not feasible due to the nature of the claim distribution [8].

The general steps of the Monte Carlo simulation begin with defining the model's parameters, which include the initial capital, premium rate, claim arrival intensity (λ), and the chosen claim size distribution. Once these parameters are established, numerous scenarios of the surplus process $U(t)$ are simulated over a specified time horizon to capture the stochastic nature of insurance operations. The probability of ruin is then estimated by calculating the proportion of simulated scenarios in which the insurer's surplus becomes negative. This approach is highly flexible, as it can accommodate various forms of claim distributions and enables sensitivity analysis on different model parameters, thereby enhancing the robustness of the results [4].

Recent research between 2020 and 2025 has significantly expanded the application of Monte Carlo simulation in actuarial risk theory, particularly for non-exponential claim size distributions [12] provide a comprehensive guide on the use of Monte Carlo methods in assessing risk return profiles under regulatory frameworks, such as Solvency II, emphasizing its role in evaluating the solvency position of insurers. More recent studies, such as [3], have investigated the estimation of ruin probabilities under heavy-tails distributions, including lognormal and gamma, demonstrating that simulation-based approaches yield more accurate estimates compared to classical analytical solutions [5]. These studies highlight the methodological shift towards incorporating more realistic claim behavior in solvency assessment models.

From an industry perspective, regulatory bodies and actuarial institutions have increasingly recognized the practical value of Monte Carlo simulation. Reports from the European Insurance and Occupational Pensions Authority [22] outline how insurers across the EU use simulation-based approaches for solvency stress testing, particularly when claim distributions deviate from exponential assumptions. Similarly, the Swiss Re Institute highlights case studies where Monte Carlo simulations has been integrated into reinsurance strategy design, enabling more precise capital allocation under extreme loss scenarios. These examples underscore that simulation methods are no longer limited to academic research but have become integral tools in operational risk management.

In North America, [23] published a technical report showcasing applications of Monte Carlo simulation in modelling ruin probability across diversified insurance portfolios. The report details practical implementations, including portfolio level aggregation of claims, dependency modelling through copulas, and scenario-based capital requirement assessments. These industry driven applications align with recent academic findings, reinforcing the notion that Monte Carlo simulation is a versatile and reliable method for evaluating insolvency risk in both life and non-life insurance contexts.

3. RESULT AND ANALYSIS

3.1 Simulation Design

To estimate the ruin probability, a Monte Carlo simulation is conducted with the following parameters. The initial capital is set at 100.000 units, while the premium income rate is fixed at 1.200 units per time unit. The claim arrival intensity is assumed to be 10 claims per unit of time, and the claim size distribution follows an exponential distribution with a mean of 10.000 units. The simulation is conducted over a time horizon of 50 units, with a total

of 10.000 iterations performed to ensure statistical stability of the results. In each iteration, the surplus process $R(t)$ is simulated from time 0 to 50, and it is observed whether ruin occurs, defined as $R(t) < 0$ for some time t .

3.2 Monte Carlo Simulation Results

Based on 10.000 Monte Carlo simulation iterations, the following result was obtained:

Table 2. Monte Carlo Simulation Results

Total Simulation	Ruins Instances	Estimated Ruin Probability
10.000	2.134	0.2134

Analysis of Table 2 shows that in 10.000 simulated scenarios, approximately 0.2134 resulted in ruin before time 50. This indicates that even with continuous premium income, randomly arriving claims can still cause a deficit.

3.3 Sensitivity Analysis

Sensitivity Analysis is conducted to examine the impact of key variables such as initial capital (u), premium rate (c), claim intensity (λ), and the distribution of aggregate claims on the ruin probability. Increases in initial capital and premium rates are shown to significantly reduce the probability of ruin. Conversely, higher claim intensity or the use of heavy-tailed claim distributions leads to a greater likelihood of insolvency. This analysis highlights that one of the most effective risk mitigation strategies involves adjusting the safety loading (θ) in premium calculations, as well as implementing optimal reserve management. To assess the influence of these parameters on ruin probability, variations in initial capital, premium rate, and claim distribution must be considered. The following table presents the impact of initial capital on ruin probability:

Table 3. Effect of Initial Capital

Initial Capital (u)	Ruin Probability
50.000	0.4462
100.000	0.2134
150.000	0.0791
200.000	0.0245

From Table 3, it is evident that higher initial capital leads to lower ruin probability. This aligns with the theory that a larger reserve can buffer extreme claim fluctuations.

Based on Table 4, higher premiums increase surpluses more quickly and reduce the likelihood of deficits,

Table 4. Effect of Premium Rate

Premium Rate (c)	Ruin Probability
1.000	0.3147
1.200	0.2134
1.400	0.1258
1.600	0.0632

Subsequently, to observe the impact of claim arrival intensity (λ) on ruin probability, a series of simulations was conducted by varying the value of λ from low to high, while keeping other parameters namely initial capital and safety loading constant. The simulation results are presented in table 5 below:

Table 5. Table of Claim Arrival Intensity

Claim Intensity	Ruin Probability		
	Eksponensial	Lognormal	Gamma
5	0.0004	0.0042	0.0000
10	0.0056	0.0156	0.0008
15	0.0123	0.0310	0.0025
20	0.0207	0.0489	0.0062

An increase in claim intensity (λ) significantly elevates the ruin probability, particularly under the lognormal distribution, which is characterized by high variance. The gamma distribution remains the most stable across

variations in λ , while the lognormal distribution exhibits the highest sensitivity to increases in claim intensity, reflecting its vulnerability to frequent and large claim burdens.

Furthermore, distributions with heavier tails such as the lognormal yield higher ruin probabilities due to the potential for rare but extremely large claims. The simulation results support the theoretical premise that ruin probability is primarily governed by the balance between initial reserve capital, premium accumulation rate, and both the intensity and magnitude of claims.

While the Cramer-Lundberg model serves as a robust theoretical framework, Monte Carlo simulation offers greater flexibility in addressing complex claim distributions and more realistic scenarios. The observation that ruin probability can be significantly reduced through adjustments to premium rates or initial capital underscores the critical role of actuaries in formulating sound financial strategies for insurance companies.

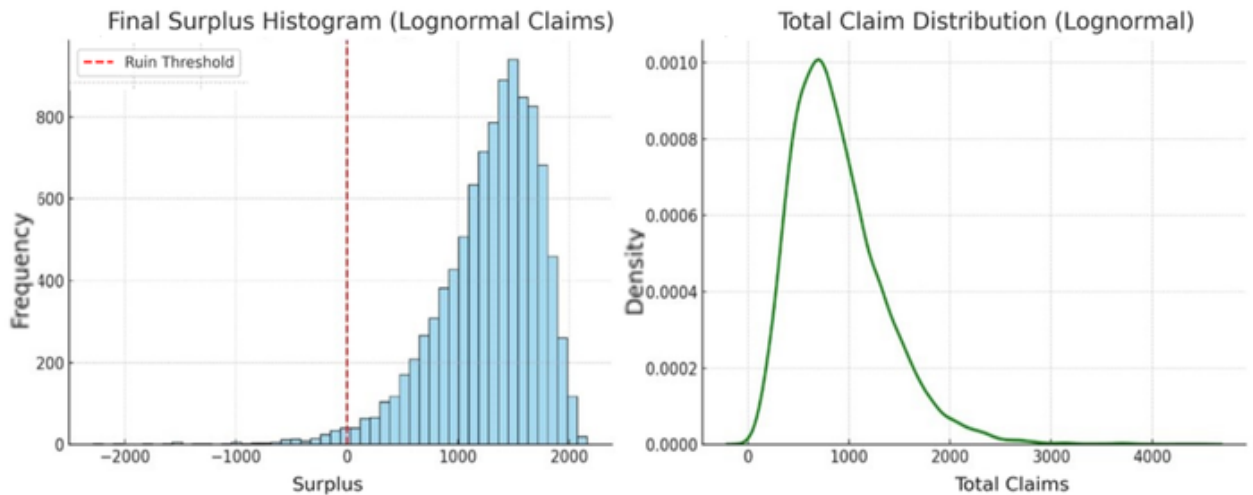


Figure 1. Simulation of the Cramer-Lundberg Model with Lognormal Claim Distributin

In Figure 1, the histogram of the final surplus shows the number of occurrences where the insurance company's surplus is above or below zero. The red line indicates the ruin threshold. The ruin threshold employed in this study is defined as the point at which the insurer's surplus becomes negative, i.e., $U(t) < 0$ at a given time period. This value is not an arbitrary figure, but rather a fixed boundary that is theoretically derived from the definition of ruin probability in the Cramer-Lundberg model [3]. In the implementation of this simulation, the threshold is expressed as a zero surplus, representing the condition in which the capital reserves are fully depleted and the insurer is unable to settle subsequent claims. Meanwhile, the density plot of total claims illustrates the shape of the total claim distribution within one year, which displays a long right tail (right-skewed) a characteristic of the lognormal distribution.

The comparison of total claim distribution shapes from the three types of distributions can be seen in Figure 2, as follows:

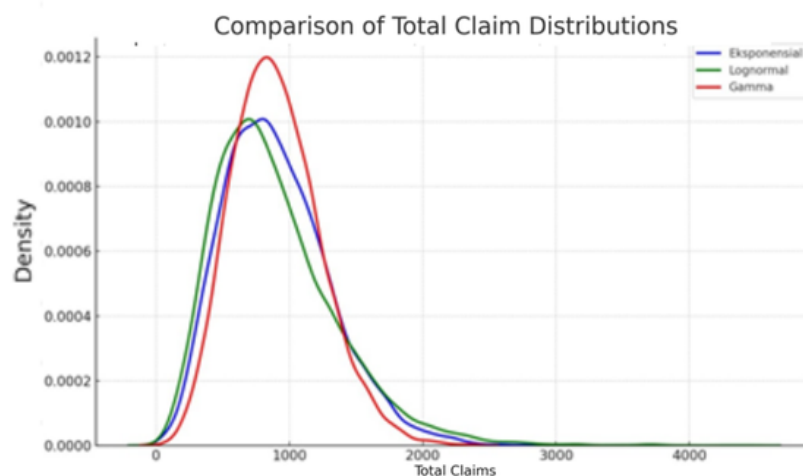


Figure 2. Comparison of Total Claim Distributions

The graph illustrates that the exponential distribution (blue) is narrow, symmetric, and exhibits low variance. In contrast, the lognormal distribution (green) is highly right-skewed with a long tail, indicating a higher risk of large claims. The gamma distribution (red) lies between the exponential and lognormal distributions it is slightly skewed but more concentrated than the lognormal.

Table 6. Estimated Ruin Probabilities Based on Monte Carlo Simulations

Claim Distribution	Ruin Probability
Exponential	0.0056
Lognormal	0.0156
Gamma	0.0008

Overall, Table 6 demonstrates that the choice of claim distribution greatly affects the estimation of ruin probability. Distributions with longer tails (e.g., lognormal) tend to yield higher ruin probabilities, while more concentrated distributions (e.g., gamma) exhibit more controlled risk levels. This highlights that heavy-tailed distributions, like the lognormal, are more susceptible to extreme claim events that can severely deplete capital reserves.

Subsequently, a descriptive statistical analysis was performed on the values of the final surplus and total claims obtained from the 10.00 simulation iterations. The summary statistics are presented as follows:

Table 7. Statistical Analysis of Surplus Values and Aggregate Claim Distribution

Total Claim Distribution	Simulations	Mean Surplus	95% CI for Mean Surplus	Median	Standard Deviation
Exponential	10.000	524.13	(517.26, 531.00)	520.45	148.22
Lognormal	10.000	498.67	(491.55, 505.79)	495.23	165.87
Gamma	10.000	512.94	(505.76, 520.12)	510.17	153.04

Table 7 reports the descriptive statistics of the final surplus for each claim size distribution, based on $N = 10.000$ Monte Carlo iterations. Alongside the mean surplus, median, and standard deviation, we include the 95% confidence interval (CI) for the mean surplus. The CI is calculated as $\bar{x} \pm 1.96 \times s/\sqrt{N}$, where $\bar{x}$ is the sample mean and s is the sample standard deviation. This provides a measure of the statistical precision of the mean estimates.

The lognormal distributions exhibit higher skewness and kurtosis, indicating a right skewed distribution of surplus values and the potential occurrence of large claims. This characteristic explains the higher ruin probability observed under the lognormal distribution.

Based on the results of the Monte Carlo simulation applied to the Cramer-Lundberg model, the influence of key parameters on the ruin probability can be summarized as follows, (a) Initial Capital (u), An Increase in initial capital consistently reduces the ruin probability, as it provides a larger buffer against extreme claim events. (b) Premium Rate (c), Higher premium rates, particularly when accompanied by an adequate safety loading coefficient (θ), accelerate surplus accumulation and lower the ruin probability, (c) Claim Arrival Intensity (λ), An increase in λ leads to more frequent claim occurrences, which, if not offset by sufficient premiums and initial capital, increases the ruin probability. (d) Total Claim Distribution, Heavy tailed distributions, such as the lognormal, tend to increase the ruin probability compared to narrower distributions such as the gamma or exponential.

Overall, an effective risk mitigation strategy combines increasing initial capital, adjusting the safety loading coefficient, and monitoring the claim size distribution to anticipate extreme risk events. The results of this study are consistent with the findings of [3], which demonstrate that increasing initial capital and ensuring adequate safety loading significantly reduce ruin probability, while long-tailed claim distributions increase insolvency risk. Furthermore, these findings align with [2], which emphasizes the importance of maintaining a balance between premium rate and claim arrival intensity to ensure insurer solvency. The primary distinction of the present study lies in the simultaneous application of Monte Carlo simulation across three distinct claim distributions, thereby providing a more comprehensive perspective.

4. CONCLUSION

Based on the research conducted using the Cramer-Lundberg model and the Monte Carlo simulation approach on three types of claim distributions exponential, lognormal, and gamma several key findings were obtained regarding the estimation of ruin probability in insurance companies. The results indicate that the choice of claim distributions significantly influences the value of ruin probability. The lognormal distribution produces the highest ruin probability due to its heavy tailed nature, whereas the gamma distribution yields the lowest probability. Moreover, the simulations also reveal that an increase in claim intensity and the use of distributions with high variance substantially raise the risk of insolvency.

From a practical standpoint, this model can be utilized by insurance companies as a decision-support tool for financial planning, premium adequacy assessment, and minimum capital reserve evaluation. By taking into account factors such as initial capital, premium rate, claim intensity, and the form of the claim distribution, companies can perform stress testing and sensitivity analysis to identify vulnerabilities within their portfolios.

Furthermore, insurance can employ this model to dynamically adjust safety loading (θ) as part of a risk management strategy that is responsive to evolving market conditions and claim profiles. Monte Carlo simulation also enables experimentation with extreme risk scenarios, which is essential in the risk management practices of both primary insurers and reinsurers. For future development, the model may be extended to incorporate factors such as investment of reserve funds, claim inflation, surplus models involving Brownian motion or jump diffusion processes, and copula-based dependency structures for multi-line insurance settings. Additionally, enhancing numerical methods and optimizing safety loading parameters through machine learning represents a promising and applicable direction in the context of digital era actuarial modelling.

Overall, the results of this study reaffirm that Monte Carlo simulation is an effective tool for enhancing the solvency assessment of insurance companies. This method enables more accurate risk measurement under various market conditions and claim scenarios, thereby supporting strategic decision making in premium determination, capital allocation, and the formulation of reinsurance policies that are more responsive to extreme risk exposures.

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