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Assessing Risk Adjustment for Non-Life Insurance under IFRS 17 (Short Version)

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Summary

This paper is a short version of SIGNORELLI, T.; CAMPANI, C.; NEVES, C. “Direct Approach to Assess Risk Adjustment under IFRS 17”, published in Revista Contabilidade & Finanças. It aims to develop a method that can be adopted by insurers to assess the risk adjustment for non-financial risks (RA) required by IFRS 17. The method takes advantage of the Collective Risk Theory and of Monte Carlo simulations and it directly returns the RA for each liability related to a group of insurance contracts: remaining coverage and incurred claims. Therefore, it does not require any additional procedure to allocate the RA between liabilities associated with insurance contracts, which constitutes an advantage over other methods. Our results show that, for large-scale portfolios, the Central Limit Theorem holds and the distributions used to assess the RA can be well approximated by the Normal distribution. Additionally, the values obtained are relatively small. This result is in line with the Law of Large Numbers.

Key Words

Risk adjustment, IFRS 17, insurance reserving, Collective Risk Theory, Monte Carlo simulation.

Contents

1. Introduction

IFRS standards aim not only to establish high quality accounting practices, but also to standardize them around the world. IFRS 17 replaced the former IFRS 4 and is devoted to determining accounting practices for insurance contracts. Its goal is to ensure that an insurer provides relevant information that faithfully represents issued insurance contracts.

Since obligations related to insurance contracts (technical provisions) usually represent the most important liabilities for these companies, this information is crucial to assess their financial position, financial performance and cash flows. While IFRS 4 was an interim standard, which permitted entities to use a variety of accounting practices for technical provisions, IFRS 17 is a robust standard that sets out principles for the recognition, measurement, presentation, and disclosure for liabilities related to insurance contracts. In this context, IFRS 17 establishes that, on the initial recognition, the carrying amount of a group of insurance contracts shall be the sum of: (1) the fulfilment cash flows; and (2) the contractual service margin (if the group of contracts is not onerous), which represents the expected present value of unearned profits. On subsequent measures, IFRS 17 requires, in general, that this carrying amount shall be the sum of: (1) the liability for the remaining coverage, which comprises the fulfilment cash flows related to future services and the contractual service margin; and (2) the liability for incurred claims, which includes the fulfilment cash flows associated with past services.

Fulfilment cash flows can be interpreted as the expected present value of future cash flows plus a risk adjustment for non-financial risks (RA), which must reflect the compensation an entity requires for bearing the uncertainty about the amount and timing of future cash flows that arise from non-financial risks.

IFRS 17 does not specify any estimation technique to determine the RA. Hence, this paper seeks to develop a method, especially designed for non-life insurance contracts, that can be easily adopted by insurers to assess the RA according to IFRS 17 directives. The main contribution of this research is to provide an innovative method that directly returns a faithful measurement of the RA for each technical provision related to a group of insurance contracts, contributing to the correct assessment of actuarial liabilities.

2. Literature Review

Cash flows associated with insurance contracts are not certain. Therefore, IFRS 17 determines that, when evaluating liabilities related to insurance contracts, insurers must assess the compensation they require for bearing the uncertainty about the amount and timing of future cash flows that arise from non-financial risks (RA).

The concept of compensation is not new in the insurance industry. In insurance pricing, the amounts charged to policyholders (premiums) are defined so that there is a small probability that future cash outflows will be greater than premiums (cash inflows). To achieve this goal, insurers assess the expected present value of future cash outflows and add a safety charge to cover risk fluctuations. This sum (pure premium) must reflect not only the expected present value of future cash outflows, but also the compensation required by insurers for bearing non-financial risks. The compensation concept brought by IFRS 17 is also related to the risk premium required by investors, when dealing with risky assets.

IFRS 17 is a principle-based standard, and it does not specify any estimation technique to determine the RA. However, the standard requires that the chosen method must be consistent with the following general principle: the more uncertain the cash flows related to a specific group of insurance contracts, the higher the RA. According to HANNIBAL (2018), there are several potential methods that meet IFRS 17 principles, but the most commonly adopted are the Cost of Capital (CoC) and Probability Distribution Generating (PDG) methods.

The CoC approach is based on the return required by shareholders. Under this method, the RA is interpreted as the compensation shareholders require to meet a targeted return on that capital. The CoC approach is the one prescribed by Solvency II to assess the risk margin.

JIANG (2020) pointed out that, when compared to the CoC approach, PDG methods have the advantage of being less dependent on assumptions such as the rate of cost of capital, capital projections and loss distribution. Additionally, COULTER (2016) argued that there are three disadvantages when applying the CoC method: (1) it does not produce a probability of sufficiency; (2) capital models generally do not consider lapse risk well enough; and (3) it is likely to be heavily reliant on regulatory capital standards.

ENGLAND *et al*. (2019) proposed a PDG method based on the claims development triangle and a bootstrap representation of MACK (1993) model. A similar method was designed by ZHAO *et al*. (2021). However, as pointed out by ENGLAND *et al*. (2019), the chain ladder technique, used to predict the lower portion of the claims development triangle, is not always the most appropriate to be used in practice. Additionally, the approach based on the claims development triangle provides an incomplete evaluation of the RA, since it only returns the RA related to the technical provision associated with incurred claims. As mentioned before, IFRS 17 requires that liabilities associated with the remaining coverage period (future services) and incurred claims (past services) must be assessed separately. Therefore, this method is not directly applicable under IFRS 17 directives, because it must be complemented by a method that assesses the RA related to the remaining coverage period (claims that have not occurred yet) and that consistently allocates each portion of the RA between both liabilities (remaining coverage period and incurred claims).

For this reason, we propose an alternative PDG method that aims to provide faithful estimates for the RA according to IFRS 17. Our method is based on the Collective Risk Theory (LUNDBERG, 1940) and takes advantage of a hybrid approach that combines two techniques accepted to estimate a probability distribution that can be used to assess the RA (CANADIAN INSTITUTE OF ACTUARIES, 2020): fitting future cash flows for non-financial risks to a suitably probability distribution and Monte Carlo simulation.

3. Methodology

3.1 The Probability Distribution of the Present Value of Aggregate Claims

The RA is directly related to the uncertainty of the present value of future cash flows associated with a specific group of insurance contracts. To estimate a probability distribution that can be used to assess it, we depart from the Collective Risk Theory, which assumes that a random process generates claims for a group of policies subject to similar risks and that this process is characterized in terms of the portfolio as a whole rather than in terms of the individual policies that comprise it.

According to CRAMÉR (1956), the mathematical formulation is based on two random variables: (1) the number of claims produced by a portfolio of policies in a given time period (N); and (2) the present value of individual claim amounts (X_i, $where\ i = 1, 2, 3, \dots, N$). The random variable that represents the present value of aggregate claims during the period under study (S) is given by:

$$S = X_1 + X_2 + X_3 + \cdots + X_N \quad (1)$$

The Collective Risk Theory is centered on two fundamental assumptions:

$X_1, X_2, X_3, \dots, X_N$ are identically distributed random variables; and

The random variables $N, X_1, X_2, X_3, \dots, X_N$ are mutually independent.

In words, the theory assumes that S corresponds to the sum of all present values of individual claim amounts ($X_1, X_2, X_3, \dots, X_N$) that occurred in a given time period. The number of terms that comprise it is not deterministic and is modeled by the random variable N, which aims to capture the frequency behavior of claims. The severity behavior of claims is modeled by X_i.

From the assumptions above, the distribution of S can be derived from the Law of Total Probability as follows:

$$F_S(x) = P(S \leq x) = \sum_{n=0}^{\infty}(P(S \leq x|N = n) \times P(N = n)) =$$

$$= \sum_{n=0}^{\infty}(P(X_1 + X_2 + X_3 + \cdots + X_N \leq x|N = n) \times P(N = n)) \quad (2)$$

Equation 2 shows that the distribution of S is totally determined by the distributions of N and X_i. However, for practical matters, it is usually not possible to derive the probability distribution of S analytically. Especially when, for a specific portfolio, large values of N assume positive probabilities and/or when the convolutions of distributions suitable for X_i cannot be calculated easily, the distribution of S does not have an analytical closed form. In these cases, it is possible to use the Monte Carlo method to generate the empirical distribution of S by simulating different values from the distributions fitted to N and X_i. The expected value and the variance of S are given by:

$$E[S] = E[X_i] \times E[N] \quad (3)$$

$$\sigma^2[S] = E[N] \times \sigma^2[X_i] + E[X_i]^2 \times \sigma^2[N] \quad (4)$$

To estimate a distribution that can be used to assess the RA of a specific group of insurance contracts, we must note that, when an insurance contract is issued, the insurer charges a deterministic premium to assume third party risks. On the other hand, claims are stochastic and cannot be certainly determined in advance. Hence, the present value of future cash outflows related to a group of insurance contracts is given by the present value of aggregate claims (S) minus the present value of premiums that have not yet been received from policyholders ($Premium$), which means that all uncertainty of future cash flows is due to S. Therefore, since S is the only source of uncertainty, the RA must be obtained from this distribution.

Two important observations must be made about the variables S and $Premium$. Firstly, under our method, S is used to assess the RA and, consequently, must include all uncertain cash outflows, which means considering not only the present values of claims, but also all other cash outflows related to them (other expenses necessary to settle claims). Secondly, we assume that $Premium$ is free of credit risk.

From the above, the RA must be obtained from the distribution of S. However, it is more convenient to work with two related variables ($\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$),which can generate loading factors that assess the compensation required by the insurer per unit of premium and per unit of the expected present value of aggregate claims. These loading factors can then be directly applied to the carrying amount of unearned premiums (unaccrued premiums related to the remaining coverage) and to the expected present value of incurred claims in order to calculate the RA values of each technical provision associated with this group of contracts: remaining coverage (future services) and incurred claims (past services).

The variable $\frac{S}{Premium_{earned}}$ can be interpreted as the present value of aggregate claims (S) per unit of earned premium ($Premium_{\,earned}$). It is an important index (loss ratio) that reflects the past general behavior of the group of insurance contracts under analysis. To estimate the distribution of $\frac{S}{Premium_{earned}}$, a convenient period of analysis must be chosen.

Claims occurred in this period are used to estimate the distributions of N, X_i and S. On the other hand, $Premium_{\,earned}$ is a deterministic variable that represents the accrued premium during the same period. The value $\mu S/Premium\ earned$ = $\frac{E[S]}{Premium\,earned}$ gives the expected portion of premiums that will be used to pay claims. When applied to the carrying amount of unearned premiums, it returns the expected present value of claims related to the remaining coverage period. A risk measure applied to this distribution ($\mathcal{M}$ ($\frac{S}{Premium_{earned}}$)) returns extreme values for the loss ratio index. Therefore, a loading factor given by $\theta_{remaining\ coverage} = \mathcal{M}$ ($\frac{S}{Premium_{earned}}$) – $\mu_{S/Premium\ earned}$ can be interpreted as a safety charge per unit of premium. When applied to the carrying amount of unearned premiums, it returns the RA for the liability related to the remaining coverage.

However, it is important to highlight that the loss ratio distribution is estimated from the past behavior of the group of insurance contracts. If changes in this behavior are not expected, the RA related to the remaining coverage can be assessed by the amount of risk per unit of premium multiplied by the carrying amount of premiums related to the remaining coverage. In other words, our method assumes that the overall behavior of the insurance portfolio will not suffer major changes. The mean and variance of the loss ratio random variable are given by:

$$E[S/Premium_{\ earned}] = \frac{E[S]}{Premium_{\ earned}} \quad (5)$$

$$\sigma^2[S/Premium_{\ earned}] = \frac{\sigma^2[S]}{{Premium_{earned}}^2} \quad (6)$$

Analogously, the rescaled random variable $\frac{S}{E[S]}$ corresponds to the present value of aggregate claims (S) per unit of its expected value ($E[S]$). Since the liability associated with incurred claims must reflect their expected present value, a risk measure applied to the distribution of $\frac{S}{E[S]}$ can be used to generate a loading factor that represents the amount of risk per unit of $E[S]$. When applied to the carrying amount of the expected present value of incurred claims, this loading factor determines the corresponding value of RA. The mean and variance of $\frac{S}{E[S]}$ are given by:

$$E[S/E[S]] = \frac{E[S]}{E[S]} = 1 \quad (7)$$

$$\sigma^2[S/E[S]] = \frac{\sigma^2[S]}{E[S]^2} \quad (8)$$

3.2 Database

The original database used here was composed of information about claims from a real Brazilian automobile insurance portfolio and it contains the id number, the date and the updated expected present value of all cash flows associated with each claim that occurred in 2020 (78,137 claims). The expected present value of future cash flows includes not only the claims themselves, but also all other expenses necessary to fulfill contractual obligations. To avoid the identification of the insurance company, the expected present value of each claim has been multiplied by a fixed factor.

3.3 The Probability Distribution of the Number of Claims

Our methodology requires a period of analysis to be specified in advance. Since automobile insurance contracts usually have a one-year coverage period in Brazil, we defined one year as the period of analysis. Therefore, S represents the distribution of the present value of aggregate claims incurred in 1 year.

To estimate the distribution of N, a sample with a reasonable number of observations is required. However, since N is a random variable that represents the number of claims in 1 year, a reasonable sample size requires the analysis of a long period. A long period, in turn, may contain old observations that do not reflect the current behavior of the insurance portfolio. To overcome this challenge, instead of estimating the probability distribution of N directly, we estimated the probability distribution of the daily number of claims (N_{daily}).

Since our sample contains data of claims incurred in 2020, we have a random sample of 366 observations of N_{daily}.

The random variable N_{daily} is discrete. Moreover, the sample space of N_{daily} is the set $\{0, 1, 2, \dots, \infty\}$. SIMON (1960) showed that, when $\sigma^2[N_{daily}] > E[N_{daily}]$, the Negative Binomial distribution is usually the most appropriate to model the number of automobile claims in a fixed period. The same results were obtained by FERREIRA (1998) for a Brazilian automobile insurance portfolio. We calculated the sample mean and variance for our database and the same relationship has been found. Therefore, the Negative Binomial distribution has been chosen as the distribution of N_{daily}. The method of moments was used to estimate its parameters.

The random variable N corresponds to the sum of claims occurred on each day of the year. Therefore, once the distribution of N_{daily} has been estimated, the random variable N can be obtained as follows:

$$N = N_{daily,1} + N_{daily,2} + N_{daily,3} + \cdots + N_{daily,366} \quad (9)$$

Since N is the sum of 366 independent and identically distributed negative binomial random variables ($N_{daily} \sim Negative\ Binomial(r, p)$), it is also a negative binomial random variable with the following parameters: $N \sim Negative\ Binomial(366 \times r, p)$. Therefore, the mean and variance of N are given by:

$$E[N] = 366 \times E[N_{daily}] \quad (10)$$

$$\sigma^2[N] = 366 \times \sigma^2[N_{daily}] \quad (11)$$

The procedure described above allows estimating the distribution of N through recent observations, reflecting the current behavior of the insurance portfolio the most reliable as possible.

3.4 The Probability Distribution of the Present Value of the Individual Claim Amount

To estimate the probability distribution of the present value of the individual claim amount (X_i), we considered each claim that occurred in 2020 (78,137 claims). The histogram of X_i revealed that its distribution is skewed to the right. Therefore, three different theoretical continuous distributions that have this characteristic (Gamma, Weibull and Lognormal) were fitted to the sample of X_i and the one with the lowest square root of the mean squared error (MSE) was chosen: Lognormal. The MSE was calculated between the probability density of the midpoints of each histogram class and the probability density of the corresponding point in the theorical distribution. The parameters of all theoretical distributions were estimated through the method of moments.

Once both distributions of N and X_i were estimated, we simulated the empirical distribution of S, $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$ using Monte Carlo methods.

3.5 Risk Measure

From the probability distributions of $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$, it is possible to quantify the RA for each technical provision associated with a group of insurance contracts (remaining coverage and incurred claims).

A risk measure is an instrument that summarizes a distribution in one single number. Several risk measures have been created over time, but not all are coherent as defined by ARTZNER et al. (1999). The Value at Risk (VaR) is the standard risk measure adopted under Solvency II. J.P. MORGAN (1996) defined it as a measure of the maximum potential change in value of a portfolio with a given probability over a pre-defined horizon. Mathematically, VaR is the α quantile of the reference probability distribution and can be expressed as:

$$VaR_{\alpha}(Y) = \inf\{y \in \mathbb{R} \mid \mathcal{F}(Y) > \alpha\} \qquad (12),$$

where $\mathcal{F}(Y)$ denotes the cumulative distribution of Y.

ARTZNER *et al.* (1999) showed that VaR does not satisfy the Subadditivity requirement. Therefore, it does not satisfy the concept of a coherent risk measure as defined by them. However, considering that it is the standard risk measure adopted under Solvency II, we assessed RA using VaR and compared the result with a coherent risk measure: the Conditional Tail Expectation (CTE).

DARKIEWICZ *et al*. (2005) recognized CTE as a very important risk measure for solvency purposes. It is defined as follows:

$$CTE_{\alpha}(Y) = E[Y \mid Y > Q_{\alpha}(Y)] \quad (13),$$

where Q_{α} denotes the α-th quantile of Y.

Once the risk measures of interest are chosen (VaR and CTE), the loading factors can be obtained as follows:

$$\theta_{remaining\,coverage} = \mathcal{M}\left(\frac{S}{Premium_{\,earned}}\right) - \mu_{S/Premium\;earned} \quad (14),$$

where $\mu_{S/Premium\;earned}$ denotes the mean of $\frac{S}{Premium_{earned}}$ and $\mathcal{M}$ is the chosen risk measure.

$$\theta_{incurred\,claims} = \mathcal{M}\left(\frac{S}{E[S]}\right) - \mu_{S/E[S]} \quad (15),$$

where $\mu S/E[S]$ denotes the mean of $\frac{S}{E[S]}$ and $\mathcal{M}$ is the chosen risk measure.

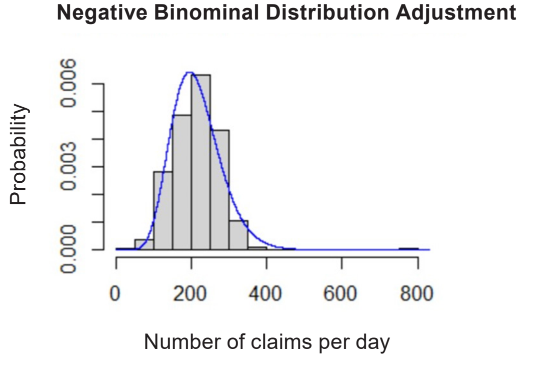
Equation 14 shows that the loading factor related to the remaining coverage can be interpreted as the amount of risk per unit of premium. Analogously, from equation 15, the loading factor associated with incurred claims represents the amount of risk per unit of $E[S]$. Therefore, when applied to the carrying amount of unearned premiums and to the expected present value of incurred claims, they provide the RA value for each liability: remaining coverage and incurred claims, respectively.

4. Results and discussion

The database used in this paper contains the id number, date and adjusted expected present value of all cash flows associated with each claim that occurred in 2020 (78,137 claims). To estimate the distribution of N_{daily}, we grouped all claims with the same date and counted the number of records on each day of the year. This procedure returned a sample of 366 observations for N_{daily}. The sample mean and the sample variance were, respectively, the following: 213.49 and 4,142.77.

SIMON (1960) showed that, when $\sigma^2[N_{daily}] > E[N_{daily}]$, the Negative Binomial distribution is usually the most appropriate to model the number of automobile claims in a fixed period. The method of moments was used to estimate the Negative Binomial distribution parameters. Once the parameters were estimated, the random variable N_{daily} was defined as $N_{daily} \sim Negative\ Binomial(r = 11.63, p = 0.0517)$. Figure 1 shows the histogram of N_{daily} and the theoretical distribution fitted to it.

Figure 1 – Histogram of the random variable N_{daily} and the theoretical distribution fitted to it ($N_{daily} \sim Negative\ Binomial(r = 11.63, p = 0.0517)$)



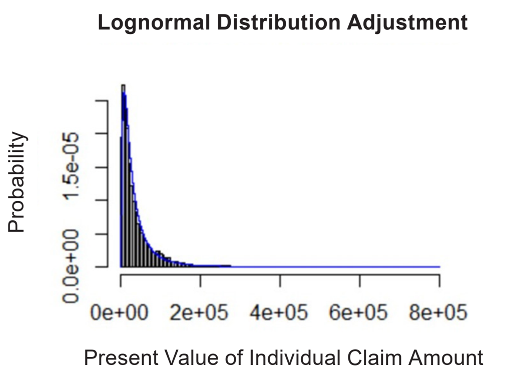
Since N is the sum of 366 independent and identically distributed negative binomial random variables ($N_{daily} \sim Negative\ Binomial(r = 11.63, p = 0.0517)$), it is also a negative binomial random variable with the following parameters:

$$N \sim Negative\ Binomial(366 \times r = 4{,}257.68, p = 0.0517).$$

To estimate the probability distribution of X_i, we considered each claim that occurred in 2020 (78,137 claims). Three different theoretical continuous distributions that have this characteristic (Gamma, Weibull and Lognormal) were fitted to the sample of X_i and the one with the lowest square root of the mean squared error (MSE) was chosen: Lognormal. The parameters of all theoretical distributions were estimated through the method of moments and the MSE was calculated between the probability density of the midpoints of each histogram class and the probability density of the corresponding point in the theorical distribution. The square root of the MSE obtained for each distribution was the following:

1.60 E-06 (Gamma), 1.40 E-06 (Weibull) and 9.07 E-07 (Lognormal). Hence, X_i has been defined as $X_i \sim Lognormal(\mu = 10.13, \sigma = 0.97)$. The parameters μ and σ correspond, respectively, to the mean and standard deviation of a normal random variable W, $where\ X_i = e^W$. Figure 2 shows the histogram of X_i and the theoretical distribution fitted to it.

Figure 2 – Histogram of the random variable X_i and the theoretical distribution fitted to it ($X_i \sim Lognormal(\mu = 10.13, \sigma = 0.97)$)



Once both distributions of N and X_i were estimated, we simulated the empirical distribution of S, $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$ using the Monte Carlo method. We proceeded as follows: 10,000 random values (N_j, $where$ $j = 1, 2, 3, \ldots, 10{,}000$) of a Negative Binomial distribution $N \sim Negative\ Binomial(366 \times r = 4{,}257.68, p = 0.0517)$ were generated. For each value of N_j, N_j random values simulating each X_i were generated from a Lognormal distribution $X_i \sim Lognormal(\mu = 10.13, \sigma = 0.97)$. Hence, the sum of all X_i values (N_j variables) represents one simulation of S. The procedure was repeated for each value N_j (10,000 times) to provide the empirical distribution of S. Finally, to obtain the distributions of $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$, each simulation of S was divided by the amount of earned premiums (multiplied by the same factor applied to the expected present value of each claim) and by $E[S]$, respectively. Figures 3 and 4 present the empirical distributions obtained for $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$ (both in percentage terms). They also show the corresponding approximations by Normal distributions: $Normal(E[100 \times S/Premium_{earned}], \sigma[100 \times S/Premium_{earned}])$ and $Normal(E[100 \times S/E[S]], \sigma[100 \times S/E[S]])$.

Figure 3 – Empirical distribution of the loss ratio (in percentage terms) and the corresponding normal approximation

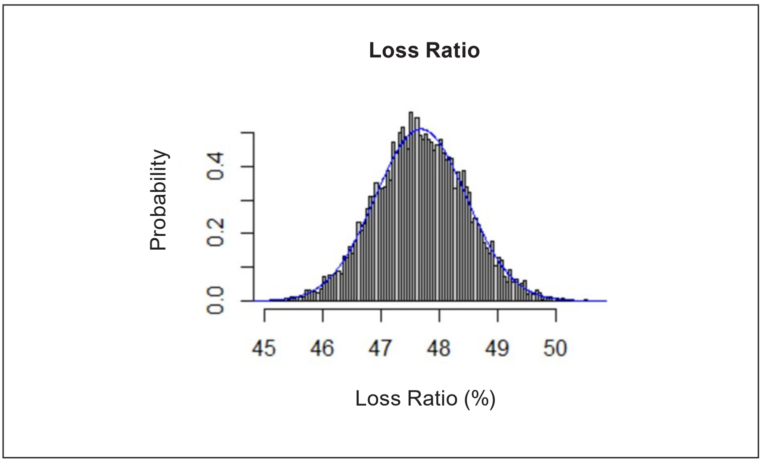
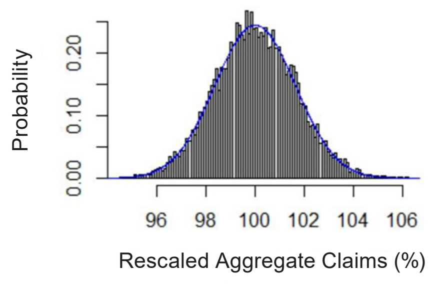


Figure 4 – Empirical distribution of $S/E[S]$ (in percentage terms) and the corresponding normal approximation



Figures 3 and 4 show that, since $E[N] = 78{,}137$ is large enough, S is obtained through the sum of many independent and identically distributed random variables (X_is). Under these conditions, the Central Limit Theorem holds and the distributions of $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$ can be well approximated by the corresponding Normal distributions. Considering these results, from now on, we decided to work with the normal approximations for the distributions of $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$ (in percentage terms).

To determine each loading factor, it is necessary to apply a risk measure to the distributions of $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$. The confidence level chosen by the insurer to determine the loading factors must reflect its risk aversion. In this paper, to illustrate how loading factors can be obtained, we adopted several different confidence levels: 70%, 80%, 90%, 95%, 97.5% and 99.5%. We also selected two different risk measures to calculate them: VaR and CTE.

For each confidence level and for each risk measure (VaR and CTE), the loading factor related to the remaining coverage was calculated using equation 14, applied to the normal approximation obtained for the distribution of $\frac{S}{Premium_{earned}}$ (in percentage terms). The results are presented in table 1.

Table 1 – Values obtained for the remaining coverage loading factor ($\theta_{remaining\ coverage}$) for each confidence level (α) and for each risk measure (VaR and CTE)

Confidence Level (α)	$\theta_{remaining\ coverage}$	
	VaR	**CTE**
α = 70.0%	0.41%	0.90%
α = 80.0%	0.66%	1.09%
α = 90.0%	1.00%	1.37%
α = 95.0%	1.28%	1.61%
α = 97.5%	1.53%	1.82%
α = 99.5%	2.01%	2.26%

From the above, we observe that the values obtained for both loading factors related to the remaining coverage are close to each other and do not exceed 3% of unearned premiums, which means that they are relatively small. This result is explained by the Law of Large Numbers, which states that, for large-scale portfolios, the risk borne by the insurer becomes lower, since it is easier to predict the behavior of future claims when aggregated.

The fulfilment cash flows related to remaining coverage is the sum of the expected present value (best estimate) of future cash flows associated with future services and the corresponding RA. This best estimate can be calculated from the loss ratio expected value, which represents the expected portion of premiums that will be used to pay off obligations arising from the remaining coverage period. When this expected value is applied to the carrying amount of unearned premiums, it provides the expected value of future cash outflows associated with the remaining coverage. The expected value of future cash outflows minus premiums not yet received by the insurer (cash inflows) provides the best estimate of future cash flows related to the remaining coverage.

Our results show that the Normal distribution provides a good approximation for the loss ratio. Therefore, there is a probability of 50% that the effective loss ratio will be lower than its expected value. In other words, if a risk adjustment is not considered, there is a 50% probability that the expected value of future cash outflows will not be enough to settle all future obligations associated with the remaining coverage period. To solve this problem, IFRS 17 determines that the RA must be added.

Considering the portfolio under analysis, if, for instance, approximately 2% of the carrying amount of unearned premiums is added to the best estimate of future cash flows, there is low probability (0.5%) that the fulfilment cash flows will not be sufficient to pay off all obligations related to the remaining coverage period. That is exactly the interpretation of the loading factor related to the remaining coverage: it is the additional compensation, per unit of premiums, required by the insurer to assume the risks of a group of insurance contracts. When multiplied by the carrying amount of unearned premiums, it provides the current value of the RA related to the remaining coverage.

Analogously, for each confidence level and for each risk measure (VaR and CTE), the loading factor related to incurred claims was calculated using equation 15, applied to the normal approximation obtained for the distribution of $\frac{S}{E[S]}$ (in percentage terms). The results are presented in table 2.

Table 2 – Values obtained for the loading factor related to incurred claims ($\theta_{incurred\ claims}$) for each confidence level (α) and for each risk measure (VaR and CTE)

Confidence Level (α)	$\theta_{incurred\ claims}$	
	VaR	CTE
α = 70.0%	0.86%	1.90%
α = 80.0%	1.38%	2.29%
α = 90.0%	2.10%	2.87%
α = 95.0%	2.69%	3.37%
α = 97.5%	3.21%	3.82%
α = 99.5%	4.21%	4.73%

The interpretation of this loading factor is similar to that presented for the one related to the remaining coverage: it is the additional amount, per unit of $E[S]$, necessary to make the probability of undervaluation of incurred claims low. For instance, if approximately 4% of the expected present value of incurred claims is added to this best estimate, there is low probability (0.5%) that the fulfilment cash flows will not be sufficient to settle obligations due to claims that have already occurred. Therefore, the loading factor related to incurred claims can be interpreted as the additional value, per unit of $E[S]$, necessary to make the probability of undervaluation of incurred claims low. When multiplied by the carrying amount of the expected present value of incurred claims, it provides the RA related to the corresponding technical provision (incurred claims).

Finally, two points deserve to be highlighted. Firstly, in line with IFRS 17 directives, our method returns two different loading factors with the following characteristic: risks with a wider probability distribution will result in higher risk adjustments for non-financial risks than risks with a narrower distribution. Secondly, it is important to note that IFRS 17 determines that the RA must be assessed for each group of insurance contracts subject to similar risks and managed together. This requirement is justified by the fact that insurers require different compensations for groups of insurance contracts with different risks. In this context, the RA of all insurance groups may not correspond to the sum of all individual RAs due to diversification effects. Therefore, the insurer must assess not only the loading factors of each group of insurance contracts, but also carefully evaluate correlations between different insurance portfolios and assess its total RA.

5. Conclusion

This paper proposes a PDG method based on the Collective Risk Theory and on Monte Carlo simulations that returns faithful measurements for the RAs related to the remaining coverage and to incurred claims.

Unlike PDG methods based on the claims development triangle, our method returns loading factors that, when applied to the carrying amount of unearned premiums and to the expected present value of incurred claims, directly provide the RA related to each technical provision (remaining coverage and incurred claims). Hence, it does not require any additional method to allocate the RA between liabilities related to insurance contracts, which constitutes an advantage over other PDG methods.

Our results show that, for large-scale portfolios, the Central Limit Theorem holds and the distributions used to assess the RA ($\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$) can be well approximated by the Normal distribution. Additionally, the values obtained for the loading factors are relatively small. This result is explained by the Law of Large Numbers.

Finally, it is worth mentioning that this paper aims to contribute to the development of the insurance market by proposing a method that can be easily adopted by practitioners to estimate the RA directly and reliably.

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