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Original Article

Direct approach to assess risk adjustment under IFRS 17*

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ABSTRACT

This paper aims to develop a method that can be adopted by insurers to assess the risk adjustment for nonfinancial risks (RA) required by International Financial Reporting Standards 17 (IFRS 17). Unlike other methods, the method proposed here directly returns the RA for each liability related to a group of insurance contracts: remaining coverage and incurred claims. Moreover, each portion of the RA is correctly allocated to the corresponding actuarial liability, which constitutes an advantage over other methods. The method follows IFRS 17 directives and contributes to standardize accounting practices of insurers around the world, thus increasing the degree of comparability between financial statements in different jurisdictions. This paper should be relevant for insurance companies, for insurance market supervisors and regulators, as well as for practitioners in general. The method takes advantage of the collective risk theory and of the Monte Carlo simulation technique to adjust probability distributions used to calculate two different loading factors that, when applied to the carrying amount of unearned premiums and to the expected present value of incurred claims, directly return the RA for each liability related to a group of insurance contracts: remaining coverage and incurred claims. Our results show that, for large-scale portfolios, the central limit theorem holds and the distributions used to assess the loading factors can be well approximated by the normal distribution. Additionally, the values obtained for each loading factor are small, which means that the RA is relatively low when compared to the carrying amount of unearned premiums and to the expected present value of incurred claims. This result is in line with the law of large numbers, which states that, for large-scale portfolios, the risk borne by the insurer becomes considerably lower, since it is easier to predict the behavior of aggregate future claims.

Keywords: risk adjustment, IFRS 17, insurance reserving, collective risk theory, Monte Carlo simulation.

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1. INTRODUCTION

The International Accounting Standards Board (IASB) is an oversight body charged with setting International Financial Reporting Standards (IFRS). IFRS aim not only to establish high quality accounting practices, but also to standardize them around the world, which improves the transparency, accountability, and efficiency of financial markets. IFRS 17 replaced the former IFRS 4 and is devoted to determining accounting practices for insurance contracts. Its goal is to ensure that an insurance, reinsurance, or pension company provides relevant information that faithfully represents issued insurance contracts. From now on, to avoid repetition, we will refer to all these entities simply as insurers.

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: (i) the fulfilment cash flows; and (ii) the contractual service margin (if the group of contracts is not onerous), which represents the expected present value of unearned profits the entity will recognize as it provides insurance contract services in the future. On subsequent measures, IFRS 17 requires, in general, that this carrying amount shall be the sum of: (i) the liability for remaining coverage, which comprises the fulfilment cash flows related to future services and the contractual service margin; and (ii) the liability for incurred claims, which includes the fulfilment cash flows associated with past services.

The fulfilment cash flows have 3 components: (i) an unbiased, current explicit and probability-weighted estimate of future cash flows that may arise as the entity fulfils insurance obligations; (ii) an adjustment to reflect the time value of money and the financial risks related to these cash flows (to the extent that the financial risks are not included in the estimates of future cash flows); and (iii) a risk adjustment for nonfinancial risks (this risk adjustment is usually simply called RA). In other words, fulfilment cash flows can be interpreted as the expected present value of future cash flows plus a RA for nonfinancial risks.

Under IFRS 17, the RA must reflect the compensation an entity requires for bearing the uncertainty about the amount and timing of future cash flows that arise from nonfinancial risks. The standard does not specify any estimation technique to determine the RA. However, it requires that the chosen method shall have the following characteristic: risks with a wider probability distribution will result in higher RAs for nonfinancial risks than risks with a narrower distribution.

IFRS 17 is a recent standard and, consequently, most of its guidelines have not been extensively explored in literature. In this context, Palmborg et al. (2021) made an important contribution by proposing a method, based on the claims development triangle, to assess the contractual service margin. England et al. (2019) and Zhao et al. (2021) also adopted the claims development triangle to build a method that aims to evaluate the RA of an insurance portfolio. However, since both methods only estimate the distribution of future cash flows associated with incurred claims, they do not provide a complete measurement of the RA, as required by IFRS 17. Instead, only the portion of the RA related to incurred claims is assessed, which means that both methods must be complemented by another one that evaluates the RA related to the remaining coverage period.

In this paper, we address the evaluation of the RA according to IFRS 17 directives. However, unlike previous research, we developed a method, especially designed for nonlife insurance contracts, that directly returns a faithful measurement of the RA for each technical provision related to a group of insurance contracts: remaining coverage (future services) and incurred claims (past services). For this purpose, it returns two different 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 reflect the past behavior of nonfinancial risks related to the group of insurance contracts under analysis and can then be directly applied to the carrying amount of unearned premiums (unaccrued premiums related to remaining coverage) and to the expected present value of incurred claims in order to calculate each corresponding RA value.

However, it is important to highlight that the method proposed here is based on the past behavior of the group of insurance contracts, which is reflected in each loading factor (loss ratio, for instance). In other words, our method assumes that portfolio characteristics will not suffer major changes. Therefore, if changes in this behavior are not expected, the method is suitable. On the other hand, if changes in this behavior are expected, the loading factors will not reflect the portfolio characteristics anymore and the method may not be suitable.

2. LITERATURE REVIEW

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

The concept of compensation required for bearing nonfinancial risks is not new in the insurance industry. In insurance pricing, for instance, 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, known as statistical premium, and add a safety charge to cover risk fluctuations. This sum, called pure premium, must reflect not only the expected present value of future cash outflows, but also the compensation required by insurers for bearing nonfinancial risks.

IFRS 17 innovated by introducing the concept of compensation in the evaluation process of technical provisions. In other words, the standard determines that insurers must evaluate the amount (compensation) they require in addition to the expected present value of future cash flows to assume the obligations (and rights) related to a specific group of insurance contracts subject to similar risks and managed together.

The compensation concept brought by IFRS 17 is also related to the risk premium required by investors when dealing with risky assets. Analogously to the compensation required by insurers for bearing risks, Arzac and Bawa (1977) derived an asset pricing theory that considers investors who maximize their expected return subject to a value at risk (VaR) constrain. Van Oordt and Zhou (2016) tested their framework and, similarly to the approach adopted by insurers, tried to capture the presence of a risk premium required to compensate potential extreme losses.

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 invested capital. In other words, it corresponds to the cost of raising capital to be held against adverse outcomes. The CoC approach is the one prescribed by Solvency II to assess the risk margin, which has been created to cover nonhedgeable risks, commonly interpreted as nonfinancial risks. Since the concepts of RA (IFRS 17) and risk margin (Solvency II) deal with the same kind of risks (nonfinancial), they present some similarities. However, there is an important difference between them: whereas Solvency II considers risks over a one-year time horizon, IFRS 17 is based on the fulfilment cash flows over their lifetime. Therefore, the latter requires careful consideration of an appropriate time horizon for risk quantification.

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 CoC rate, capital projections, and loss distribution. Additionally, Coulter (2016) argued that there are three disadvantages when applying the CoC method: (i) it does not produce a probability of sufficiency; (ii) capital models generally do not consider lapse risk well enough; and (iii) it is likely to be heavily reliant on regulatory capital standards. In line with both, England et al. (2019) defended that PDG methods are the most straightforward approach to calculating the RA under IFRS 17.

The RA assessment through PDG methods requires two different steps. Firstly, a probability distribution that can be used to assess the RA must be estimated. Secondly, a risk measure must be applied to this distribution. According to the Canadian Institute of Actuaries (2020), to generate a probability distribution, different methods may be considered: (i) fit future cash flows for nonfinancial risks to a suitably probability distribution; (ii) Monte Carlo simulation; (iii) bootstrapping; and (iv) scenario modeling.

In this context, several studies addressed the issue of estimating the probability distribution of the outstanding claims liabilities (future cash outflows related to incurred claims). B. Carvalho and J. V. Carvalho (2019) used bootstrapping techniques to estimate it. Although the authors did not intend to assess the RA related to incurred claims, their method can be adopted as a first step to evaluate it because a risk measure applied to the distribution of outstanding claims liabilities gives the RA associated with the technical provision of incurred claims.

To assess the RA according to IFRS 17 directives, England et al. (2019) proposed a PDG method based on the claims development triangle and a bootstrap representation of Mack (1993) model to estimate the probability distribution of the outstanding claims liabilities. A similar method, also based on the claims development triangle, was designed by Zhao et al. (2021), who developed and customized the paid-incurred chain (PIC) model proposed by Merz and Wüthrich (2010) to predict future claims and to generate the same probability distribution (outstanding claims liabilities). Methods based on the claims development triangle are suitable for nonlife insurance contracts, for which the chain ladder technique often provides reasonable forecasts for outstanding claims liabilities (under the assumption that patterns in claims activities in the past will continue to be observed in the future).

However, for life long-term insurance contracts, future cash flows are directly related to variables such as mortality and longevity. Therefore, the distribution of future cash flows requires modeling changes in these variables, which means that a different approach must be adopted. In this context, Chevallier et al. (2018) proposed a method for life insurance portfolios that can be used to estimate the confidence level required by IFRS 17, when the RA is assessed through a technique other than PDG methods (CoC, for instance).

It is important to highlight that, 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, as in England et al. (2019) and Zhao et al. (2021), 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, the claims development triangle approach 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).

To fill this gap, we propose an alternative PDG method that aims to provide faithful estimates for both components of the RA (remaining coverage and incurred claims) according to IFRS 17. As well as England et al. (2019) and Zhao et al. (2021), it is suitable for nonlife insurance contracts. However, instead of using the claims development triangle, our method is based on the collective risk theory and takes advantage of a hybrid approach that combines two of the four possibilities described above to estimate a probability distribution that can be used to assess the RA (fit future cash flows for nonfinancial risks to a suitably probability distribution and Monte Carlo simulation).

The collective risk theory was initially proposed by Lundberg (1940) with his pioneering work on the compound Poisson distribution. Instead of the Poisson distribution, Simon (1960) used the negative binomial distribution to model the number of automobile accidents by a collection of policyholders in a fixed period. The collective risk theory assumes that a random process generates claims for a portfolio of policies 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 (Bowers et al., 1997). Two random variables constitute the basic building blocks of this theory: (i) the number of claims produced by a portfolio of policies in a given time period (N); and (ii) the present value of individual claim amounts (X_i). The collective risk theory is general and does not impose strong restrictions to the number of claims and/or the present value of individual claim amount random variables. This flexibility allows it to generate a variety of distributions for the present value of aggregate claims (S).

However, for practical matters, it is generally not feasible to derive the distribution of S analytically [from the distributions of the number of claims (N) and the present value of individual claim amount (X_i)]. To overcome this challenge and estimate a probability distribution that can be used to assess the RA, we simulated different values from the distributions fitted to N and X_i using the Monte Carlo method.

3. METHODOLOGY

3.1 The Probability Distribution of the Present Value of Aggregate Claims

The assessment of the RA through PDG methods requires two different steps. Firstly, a probability distribution that can be used to assess the RA must be estimated. Then, a risk measure must be applied to this distribution.

The RA is a compensation required by insurers for bearing nonfinancial risks. Therefore, it 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 the RA, 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: (i) the number of claims produced by a portfolio of policies in a given time period (N); and (ii) the present value of individual claim amounts (X_i, where $i = 1, 2, 3, \dots, N$). From now on, we will refer to this variable simply as X_i and we restate that this is calculated in terms of present values. Hence, the random variable that represents the present value of aggregate claims generated by the portfolio during the period under study (S) is given by:

$$S = X_1 + X_2 + X_3 + \ldots + X_N \tag{1}$$

The collective risk theory is centered on two fundamental assumptions:
(i) $X_1, X_2, X_3, \dots, X_N$ are identically distributed random variables; and (ii) the random variables $N, X_1, X_2, X_3, \dots, X_N$ are mutually independent.

In words, the theory assumes that the random variable 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 (claims) that comprise this sum is not deterministic and is modeled by the random variable N, which aims to capture the frequency behavior of claims associated with the portfolio under study. On the other hand, the severity behavior of claims is modeled by the random variable X_i. Therefore, the random variable S is totally determined by both these random variables.

From the assumptions above, the distribution of the present value of aggregate claims (S) can be derived from the law of total probability as follows:

$$\begin{aligned} F_S(x) = P(S \le x) &= \sum_{n=0}^{\infty} \big(P(S \le x | N = n) \times P(N = n) \big) = \\ &= \sum_{n=0}^{\infty} \big(P(X_1 + X_2 + X_3 + \ldots + X_N \le x | N = n) \times P(N = n) \big) \end{aligned} \tag{2}$$

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 the present value of individual claim amount random variable (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.

An alternative approach, which usually provides good approximations for the distribution of S, takes advantage of the central limit theorem and is based on the fact that, for large-scale portfolios, the expected number of claims ($E[N]$) is large and, consequently, S is obtained through the sum of a large number of independent and identically distributed random variables X_is. When these conditions apply, the central limit theorem states that the distribution of S can also be well approximated by a normal distribution with the following parameters: $Normal(E[S], \sigma[S])$.

Although, for practical matters (such as for large-scale insurance portfolios), the distribution of the present value of aggregate claims (S) generally cannot still be derived analytically, it is possible to show that its expected value and its variance depend only on the expected values, and variances of N and X_i 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*). For simplicity, when determining the present value of future cash outflows, we do not consider fixed and variable overheads directly attributable to fulfilling obligations associated with insurance contracts (accounting, human resources, for instance).

Since IFRS 17 establishes that only issued contracts must be considered when evaluating technical provisions (and, consequently, the RA), *Premium* is a deterministic variable (premiums of issued contracts are already known), 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 e *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 the claims themselves, but also all other cash outflow related to them (other expenses necessary to settle claims). Other cash outflows, such as commercial expenses, may be disregarded because they are usually deterministic and do not provide any kind of uncertainty. Secondly, we assume that *Premium* is free of credit risk (deterministic variable).

From the stated 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 are able to 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 reflect the nonfinancial risks of the group of insurance contracts under analysis and can then be directly applied to the carrying amount of unearned premiums (unaccrued premiums related to 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 ($Premium_{\text{earned}}$). It is an important index, called loss ratio, which 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 consequently, S. On the other hand, $Premium_{\text{earned}}$ 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 ($\mathcal{M}\left(\frac{S}{Premium_{earned}}\right)$) returns extreme values for the loss ratio index. Therefore, a loading factor given by $\theta_{remaining\ coverage}=\mathcal{M}\left(\frac{S}{Premium_{earned}}\right)-\mu_{S/Premium_{earned}}$ 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 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 remaining coverage can be assessed by the amount of risk per unit of premium multiplied by the carrying amount of premiums related to 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, the same procedure described above can be adopted to assess the RA related to incurred claims. In other words, 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:

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

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

In the next sections, we describe the database used to assess the RA of a real portfolio of automobile insurance policies managed by a Brazilian insurer. Then, we explain how the distributions of the number of claims (N) and the present value of the individual claim amount (X_i) were estimated from this database. Finally, we discuss possible risk measures that can be applied to the distributions of $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$, in order to generate loading factors that can be used to assess the RA for both technical provisions related to a group of insurance contracts (remaining coverage and incurred claims).

3.2 Database

The original database for the analysis was composed of information about claims from a real automobile insurance portfolio managed by a Brazilian insurer 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, which has not allowed us to do so, 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, from now on, S represents the distribution of the present value of aggregate claims incurred in one 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 one year, a reasonable sample size requires the analysis of a long period. A long period sample, 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 $\{0, 1, 2, \ldots, \infty\}$. 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 accidents by a collection of policyholders 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 ($\sigma^2[N_{daily}] > E[N_{daily}]$). Therefore, the negative binomial distribution has been chosen as the distribution of N_{daily}. The method of moments has been used to estimate its parameters and adjust it to the database.

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:

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

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) has been 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 theoretical distribution. The parameters of all theoretical distributions were estimated through the method of moments.

Once both distributions of the number of claims per year (*N*) and the present value of individual claim amounts (X_i) were estimated, we simulated the empirical distribution of *S*, $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$ using Monte Carlo methods. We proceeded as follows: 10,000 random values (N_j, where j = 1, 2, 3, …, 10,000) of a negative binomial distribution *N~Negative Binomial* (366 x *r,p*) were generated. The parameters *r* and *p* were obtained from the distribution fitted to N_{daily}, the number of claims per day. Each value N_j represents one simulated value for the random variable *N*, the number of claims per year. For each value of N_j, N_j random values simulating each X_i were generated from a lognormal distribution X_i ~ *Lognormal* (μ, σ). The parameters μ and σ correspond, respectively, to the mean and standard deviation (SD) of a normal random variable *W* ($X_i = e^W$) and were obtained from the distribution fitted to X_i, the present value of individual claim amounts. 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) in order to provide the empirical distribution of *S*. We tested larger numbers of simulations and we could confirm that 10,000 times suffice for the objectives of this analysis. 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 the expected value of *S* (*E*[*S*]), respectively.

3.5 Risk Measure

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

As previously said, under IFRS 17 framework, the RA must reflect the compensation that an entity requires for bearing the uncertainty about the amount and timing of future cash flows that arise from nonfinancial risks. Therefore, a risk measure is required to assess the compensation required by the insurer to assume these nonfinancial risks. Additionally, considering that the RA is the compensation required by the insurer, it is directly related to the safety charge typically used to cover risk fluctuations in insurance pricing, which means that the confidence level established for the risk measure must be consistent with the confidence level adopted to determine the safety charge used to calculate pure premiums.

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 VaR is the standard risk measure adopted under Solvency II. J. P. Morgan and Reuters (1996) defined it as a measure of the maximum potential change in value of a portfolio with a given probability over a predefined horizon. Mathematically, VaR is the α quantile of the reference probability distribution and can be expressed as follows:

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

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

Artzner et al. (1999) showed that, although VaR satisfies translation invariance, positive homogeneity, and monotonicity properties, it does not satisfy the subadditivity requirement. Therefore, it does not satisfy the concept of a coherent risk measure as defined by them. However, since it is one of the most used risk measures, and considering that it is the standard risk measure adopted under Solvency II, we assessed RA using VaR and compared the result with another risk measure that satisfies all properties above: 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:

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

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

Once the risk measures of interest are chosen (VaR and CTE), the loading factors that will be applied to the carrying amount of unearned premiums and to the expected present value of incurred claims 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 the $\frac{S}{Premium_{earned}}$ random variable and $\mathcal{M}$ is the chosen risk measure (VaR or CTE).

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

where $\mu_{S/E[S]}$ denotes the mean of the $\frac{S}{E[S]}$ random variable and $\mathcal{M}$ is the chosen risk measure (VaR or CTE).

Equation 14 shows that the loading factor related to 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 $E[S]$, the expected value of 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), based on data from a real insurance company. 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 the variable 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 accidents in a fixed period. The same results were obtained by Ferreira (1998) for a Brazilian automobile insurance portfolio. The method of moments has been used to estimate the negative binomial distribution parameters and adjust it to the data. Once the parameters were estimated, the random variable N_{daily} was defined as N_{daily}~*Negative Binomial (r = 11.63, p = 0.0517)*. Figure 1 shows the histogram of N_{daily} and the theoretical distribution fitted to this random variable.

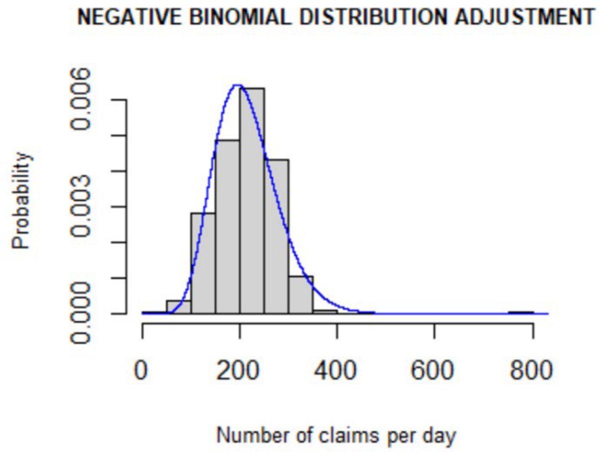

Figure 1 *Histogram of the random variable N_{daily} and the theoretical distribution fitted to it (N_{daily}~Negative Binomial (r = 11.63, p = 0.0517))*

Source: *Elaborated by the authors.*

Since N is the sum of 366 independent and identically distributed negative binomial random variables (N_{daily}~*Negative Binomial (r = 11.63, p = 0.0517)*), it is also a negative binomial random variable with the following parameters: *N~Negative Binomial (366 × r = 4,257.68, p = 0.0517)*.

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 MSE has been 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 theoretical 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, the random variable X_i has been defined as X_i~Lognormal(μ = 10.13, σ = 0.97). The parameters μ and σ correspond, respectively, to the mean and SD 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 this random variable.

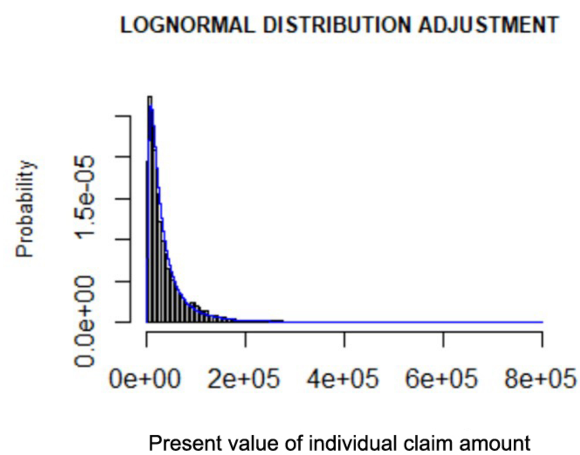

Figure 2 *Histogram of the random variable X_i and the theoretical distribution fitted to it (X_i~Lognormal(μ = 10.13, σ = 0.97))*
Note: *The lognormal distribution presented the lowest square root of the mean squared error (MSE).*
Source: *Elaborated by the authors.*

Once both distributions of the number of claims per year (N) and the present value of individual claim amounts (X_i) were estimated, we simulated the empirical distribution of S, $\frac{S}{Premium_{earned}}$ and $\frac{S}{E[S]}$, using Monte Carlo simulation technique. The R language has been adopted for this purpose. We proceeded as follows: 10,000 random values (N_j, where j = 1, 2, 3, …, 10,000) of a negative binomial distribution N~*Negative Binomial*(366 × r = 4,257.68, p = 0.0517) were generated. Each value N_j represents one simulated value for the random variable N. For each value of N_j, N_j random values simulating each X_i were generated from a lognormal distribution X_i~*Lognormal*(μ = 10.13, σ = 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) in order 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 the expected value of S ($E[S]$), respectively. Figures 3 and 4 present the empirical distributions obtained for the random variables $\frac{S}{Premium_{earned}}$ 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*($E[100 \times S/E[S]]$, $\sigma[100 \times S/E[S]]$).

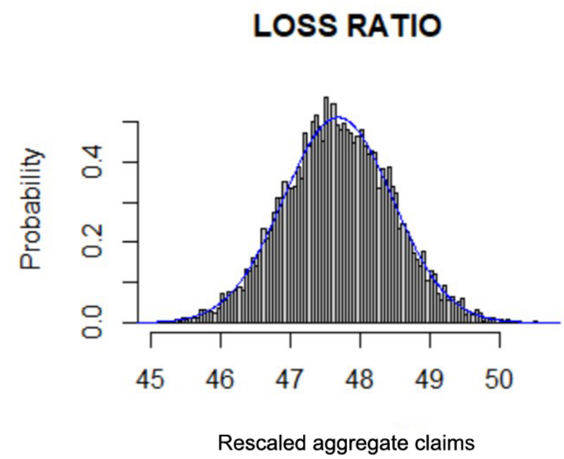

Figure 3 *Empirical distribution of the loss ratio (in percentage terms) and the corresponding normal approximation given by Normal(E[100 X S/Premium$_{earned}$], σ[100 X S/Premium$_{earned}$])*

Source: *Elaborated by the authors.*

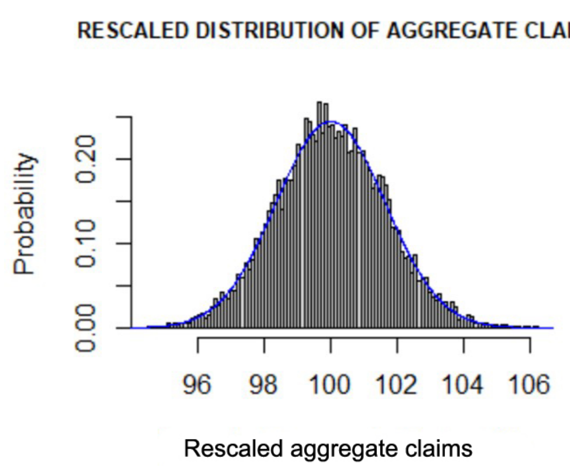

Figure 4 *Empirical distribution of the random variable S/E[S] (in percentage terms) and the corresponding normal approximation given by Normal(E[100 X S/E[S]], σ[100 X S/E[S]])*

Source: *Elaborated by the authors.*

Figures 3 and 4 show that, since the expected number of claims ($E[N] = 78{,}137$) is large enough, S is obtained through the sum of a large number of 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, given by: $Normal(E[S/Premium_{earned}], \sigma[S/Premium_{earned}])$ and $Normal(E[S/E[S]], \sigma[S/E[S]])$, respectively. 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 $\frac{S}{E[S]}$. Once the loading factors are defined, they can be multiplied by the carrying amount of unearned premiums and to the expected present value of incurred claims in order to calculate the RA for each technical provision: remaining coverage and incurred claims. Under IFRS 17 framework, the RA must reflect the compensation that an entity requires for bearing the uncertainty about the amount and timing of future cash flows that arise from nonfinancial risks. Therefore, it is directly related to the safety charge typically used to cover risk fluctuations in insurance pricing, which means that the confidence level established for the risk measure must be consistent with the confidence level adopted to determine the safety charge used to calculate pure premiums. In other words, 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 in order to calculate them: VaR and CTE. VaR was chosen because it is the standard risk measure adopted under Solvency II. Although commonly used by insurers, VaR is not a coherent risk measure as defined by Artzner et al. (1999). For this reason, we also assessed the loading factors using CTE, which is a coherent risk measure.

For each confidence level and for each risk measure (VaR and CTE), the loading factor related to 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 [value at risk (VaR) and conditional tail expectation (CTE)]

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

Source: *Elaborated by the authors.*

In Table 1, we see that the values obtained for both loading factors related to 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.

Hence, in practical terms, the technical provision related to remaining coverage (future services) would be given by the sum of two components: (i) the fulfilment cash flows; and (ii) the contractual service margin (considering that the portfolio is not onerous). The first component (fulfilment cash flows) is the sum of the expected present value (best estimate) of future cash flows related to remaining coverage 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 (future claims and other expenses). When this expected value (loss ratio) is applied to the carrying amount of unearned premiums, it gives the expected value of future cash outflows associated with remaining coverage. The expected value of future cash outflows less premiums not yet received by the insurer (cash inflows) gives the best estimate of future cash flows related to remaining coverage.

Our results show that the normal distribution provides a good approximation for the loss ratio. Therefore, there is 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 a RA must be added.

The confidence level chosen by the insurer (which reflects its risk aversion) defines the probability that the fulfilment cash flows will not be sufficient to pay off all obligations related to the remaining coverage period. Considering the portfolio under analysis, if, for instance, approximately 2% of the carrying amount of unearned premiums are summed 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 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 gives the current value of the RA related to remaining coverage.

The last component of the technical provision associated with remaining coverage is the difference between the amount of unearned premiums and the fulfilment cash flows. It represents the profit that the insurer expects from this group of insurance contracts and, consequently, must be recognized in the income statement as services are provided.

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 [value at risk (VaR) and conditional tail expectation (CTE)]

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

Source: *Elaborated by the authors.*

The interpretation of this loading factor is similar to that presented for the one related to remaining coverage: it is the additional amount, per unit of the expected present value of aggregate claims ($E[S]$), 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 summed 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 the expected present value of aggregate claims ($E[S]$), 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 gives the RA related to the corresponding technical provision (incurred claims).

The results presented above show that the loading factors are small, which means that RA values are relatively low when compared to the carrying amount of unearned premiums and to the expected present value of incurred claims. This result is in line with the ones obtained by England et al. (2019) and Zhao et al. (2021) for the RA related to incurred claims. Although associated with different insurance portfolios, as mentioned before, it is expected 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. However, it should be noted that, although consistent with the results obtained by England et al. (2019) and Zhao et al. (2021), our results are associated with data from one insurance company, which constitutes a limitation. Furthermore, the data, from which the loading factors were estimated, refer to a period of one year. Depending on the portfolio under analysis, a longer period may be more appropriate.

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 RAs for nonfinancial 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. Thus, depending on the correlations between groups of insurance contracts, the total RA may be lower than that sum. 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 simulation techniques that returns faithful measurements for the RAs related to remaining coverage and to incurred claims. The developed methodology contributes to the correct assessment of technical provisions. Since obligations related to insurance contracts (technical provisions) usually represent the most important liabilities for insurers, this information is crucial to evaluate their financial position, financial performance, and future cash flows.

In line with IFRS 17 directives, it returns two different loading factors with the following characteristic: risks with a wider probability distribution will result in higher RAs for nonfinancial risks than risks with a narrower distribution. Moreover, 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 give the RA related to each technical provision (remaining coverage and incurred claims). Hence, it not only provides a complete assessment of the RA, but also consistently allocates its components between both liabilities (remaining coverage and incurred claims), which constitutes an advantage over other PDG methods.

However, it is important to highlight that the method proposed here considers the past behavior of the group of insurance contracts. If changes in this behavior are not expected, the RAs related to remaining coverage and incurred claims can be assessed using each loading factor multiplied by the carrying amount of unearned premiums and by the expected present value of incurred claims. On the other hand, if changes in this behavior are expected, our method may not be suitable anymore, since it assumes that portfolio characteristics will not suffer major changes.

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 small, which means that RA values are relatively low when compared to the carrying amount of unearned premiums and to the expected present value of incurred claims. As discussed in the paper, this result is explained by the law of large numbers, which states that, for these portfolios, the risk accepted by the insurer becomes lower, since it is easier to predict the behavior of future claims when aggregated.

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 for each technical provision associated with a group of insurance contracts (remaining coverage and incurred claims). When the insurer segregates its portfolio into different groups of insurance contracts, it is necessary to assess the correlation between them to calculate the total amount of the RA. Since the method follows IFRS 17 directives, it contributes to standardize the accounting practices of insurers around the world, which constitutes one of the most important objectives of IFRS: increase the degree of comparability between financial statements in different jurisdictions. Thus, this paper should be relevant for insurance companies, for insurance market supervisors and regulators, as well as for practitioners in general.

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