# Estimating Risk Adjustment Based on IFRS 17 Framework Using Risk Measures Approach Applied to an Egyptian Non-life Insurance Company

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## Abstract

The International Financial Reporting Standards for insurance contracts (IFRS 17) established principles for the recognition, measurement, presentation, and disclosure of insurance contracts. A critical component of IFRS 17 is the non-financial risk adjustment (RA). Although the risk adjustment must meet certain criteria, the specific estimation method is left to the discretion of the insurer. This study aims to apply risk measures (quintiles) techniques for estimating the risk adjustment.

This research incorporates bootstrap simulation techniques based on Mack's (1993) model to evaluate lifetime reserve risk for (Marine Cargo, Inland, Marine Hull, and Fire) of an Egyptian non-life insurer through the duration of 2017-2022. Furthermore, the study estimates the risk adjustment using percentile-based risk measures (Value at Risk, Tail Value at Risk, and Proportional Hazard Transform) derived from simulated predictive distributions. Additionally, the correlation between the lines of business is considered, as required for IFRS 17 risk adjustment estimation.

The findings of this research contribute to the existing literature by providing a comparative analysis of risk adjustment methodologies under different risk measure techniques. Additionally, the risk adjustment can be reduced according to the diversification benefit that considers the dependence between different lines of business.



**Key words:**

IFRS 17, Risk Adjustment, Risk measures, Diversification Benefit

## 1. Introduction

IFRS 17 is a universal and essential international standard establishing the accounting for an insurer's activities created by a board. It replaces IFRS 4—an interim customary. IFRS 4 does not impose the measure of insurance contracts and permits firms to use native accounting necessities (national GAAP), or variations of these necessities, to measure their insurer's activities. (Board, 2017)

IFRS 17 is characterized by a principles-based approach, contrasting with the more rule-based nature of previous accounting standards. Consequently, IFRS 17 offers fewer specific directives for implementation, necessitating insurers to interpret the standards and disclose these interpretations. This requirement leads insurers to develop numerous interpretations, which subsequently impact the information prepared and communicated to financial stakeholders regarding the financial performance of insurance contracts and the company's financial position. Insurers reporting under IFRS 17 must provide justifications for certain decisions in an auditable manner. This transparency enhances the ability of financial stakeholders to make more reliable comparisons among insurers. (Koetsier, 2018)

An explicit and important element defined in IFRS 17, for which disclosure is mandatory, is the risk adjustment for non-financial risk (RA). This represents the required compensation by the insurance company for the uncertainty in non-financial risks in the expected insurance contract cash-flows. The RA is an explicit part of the insurance contract liability. (Signorelli, 2022)

IFRS 17 adopts a principles-based approach, introducing a degree of subjectivity in its application. Although the principle of the Risk Adjustment (RA) is outlined in the standard, specific calculation methods are not prescribed. Consequently, insurers must develop methodologies that reflect their unique risk tolerance levels. To foster the generation of meaningful and comparable financial performance information across companies, IFRS 17 requires insurers to disclose their methodologies in a manner that is auditable. (OLIVEIRA, 2020)

The main techniques used for risk adjustment estimation are the quintile technique and cost of capital technique. Quintile techniques e.g.(VaR, TVaR, PHT) depend on generating a probability distribution of discounted future cash flows involves employing simulation techniques such as Monte Carlo and bootstrapping. The research will consider the following risk measures: (AZEVEDO, 2021)

- **<u>Value at Risk (VaR)</u>**

Value at Risk, in its broadest sense, "is a statistic that measures and quantifies the level of financial risk within a firm, portfolio, or position across a specific time frame," which the insurer may use to assess the magnitude and frequency of potential losses in portfolios. The value derived by this metric represents, with a given degree of confidence, an insurer's expected future cash flows in the context of measuring the groups of insurance contracts. According to the criteria of IFRS 17, the higher the confidence interval, the more uncertain and risky the situation is.

$VaR_{\alpha}(X)$ is the α-percentile of X, i.e.,

$$VaR_{\alpha}(X) = F_x^{-1}(\propto) = \inf \{x \in [0, \infty) : F_x(x) \geq \propto\} \quad (1)$$

There is no single correct confidence level to use when applying IFRS 17. However, insurers can check trends in the insurance market for guidance. For example, Solvency II uses a VaR of 99.5% to calculate its capital requirements. However, this confidence level cannot be used for IFRS 17, as Solvency II only considers a one-year time horizon, while IFRS 17 considers the entire duration of future cash flows. If the Solvency II confidence level were used for IFRS 17, it would result in a huge risk adjustment.

- **<u>Tail Value at Risk (TVaR)</u>**

Tail value-at-risk (TVaR) is a risk measure that is calculated by identifying the expected value of all losses that exceed a given percentile level. TVaR is straightforward to calculate and can be used to assess the risk of both skewed and extreme distributions. Additionally, TVaR is a coherent risk measure; it satisfies certain mathematical properties that make it a reliable measure of risk. TVaR can also be used to allocate risk to sub-groups, which can be useful for risk management purposes. (P.D. England, 2019)

The equation for TVaR at the α-percentile of X, i.e.,

$$TVaR_{\propto}(X) = E[X \setminus X > VaR_{\alpha}(X)] = \frac{1}{1-\propto}\int_{\propto}^{1} VaR_{u}(x)du \qquad (2)$$

Tail value-at-risk (T-VaR) and value-at-risk (VaR) are both risk measures that are used to quantify the potential loss of an asset or portfolio. However, they differ in the way that they calculate risk. VaR is the expected loss that will not be exceeded with a certain confidence level, while T-VaR is the expected loss that will be exceeded by a certain confidence level.

T-VaR is a more comprehensive risk measure than VaR because it takes into account the tail of the probability distribution. This means that T-VaR is more sensitive to extreme losses than VaR. Additionally; T-VaR is a coherent risk measure, which means that it satisfies certain mathematical properties that make it a reliable measure of risk.

However, T-VaR is also a more complex risk measure than VaR. This means that it can be more difficult to calculate and interpret. Additionally, T-VaR may not be as widely used as VaR because it is not as well-understood.

- **Proportional hazards transform**

The proportional hazards transform (PHT) is a risk measure initially introduced by (Wang, 1995) within the insurance context. The PHT is calculated by transforming the probability distribution of a loss into a new distribution that has a constant hazard rate. This transformation has the effect of increasing the weights of the extreme losses, which makes the PHT more sensitive to skewness and extremes than other risk measures, such as TVaR.

Given a non-negative loss random variable X, with survival function $S_x(u)$ ,such that

$$S_x(u) = P\{X > u\} = 1 - P\{X \leq u\} \qquad (3)$$

Then, $E(X) = \int_0^\infty S_x(u)\,du$

The PH-mean with parameter ρ is given by$H_\rho(x)$, where

$$H_\rho(x) = \int_0^\infty [S_x(u)]^{\frac{1}{\rho}} du \qquad (for\ \rho \geq 1) \qquad (4)$$

Where, the PH-mean refers to the expected value under the transformed distribution.

The PHT is also a coherent risk measure; it satisfies certain mathematical properties that make it a reliable measure of risk. Additionally, the PHT can be used to allocate risk to sub-groups, which can be useful for risk management purposes.

## 2. Literature Review

This section provides a summary of literatures that related to the reserve risk and the implementation of IFRS 17.

The starting point of many researches depends on (Mack, 1993), who derived a distribution-free formula for estimating the standard error of the chain ladder reserve method. These results were compared with various moment-based methods through numerical application.

(Renshaw, 1998) developed a statistical model for the chain ladder method using the generalized linear model and quasi-likelihood techniques, incorporating negative incremental claims in reserve estimation.

(England P. a., 2002) presented several stochastic models for reserve calculation in non-life insurance, smoothing the run-off triangle development and tail parameters. They also explored the Bornhuetter-

Ferguson method through a Bayesian model, providing a full predictive distribution for reserve outcomes.

In another study by (England, 2002),the reserving error was predicted using a simple computational method based on a generalized linear model and the bootstrap technique. This study compared the outcomes of the bootstrap technique with other stochastic methods and Mack's distribution-free approach.

(England, 2006) extended the 2002 study, demonstrating how to obtain predictive distributions of outstanding insurance liabilities through bootstrap or Bayesian techniques. The analyses relied on Mack's dataset, allowing for negative increments, and the Bayesian technique used Markov-chain Monte Carlo methods. A comparison between Bootstrap and Bayesian techniques was also provided.

In (P.D. England, 2019)**,** the research aimed to apply both simulation and analytic techniques to estimate and connect the reserve risk in non-life insurance upon the duration of liabilities and the one-year perspective required under Solvency II requirements. The research depended on the model of (Mack, 1993), though the results have wider applicability. The distribution can be obtained through a recursive re-reserving technique.

The research found that the risk margin under Solvency II requires at least, VaR at 99.5% applied to CDRs distribution across one- year time horizon by using suitable risk measures.

In (Diyaolu, 2021), The research aimed to provide a risk adjustment technique for the Workers Compensation line of business (WC LoB) under IFRS 17 requirements. It presented the fundamental measurement approaches, with a particular focus on the Premium Allocation Approach (PAA) under IFRS 17, which addresses only the Liability for Incurred Claims (LIC), encompassing incurred claims or expired risks. The study also examined the impact of risk adjustment under IFRS 17 standards on the financial positions of insurance companies.

(Signorelli, 2022) developed a direct approach to enable insurers to evaluate the risk adjustment required by IFRS 17 for a collection of non-life insurance contracts. Unlike traditional methods that rely solely on the claims development triangle for incurred claims, this approach considers both remaining coverage and incurred claims in the risk adjustment evaluation. The study adopted the probability distribution generating (PDG) method, based on collective risk theory, utilizing Monte Carlo simulation and risk measures such as Value at Risk (VaR) and Conditional Tail Expectation (CTE).

(Elsayed, Nasr, & Seyam, 2024) analyzed the effect of IFRS 17 implementation on the reserve management in Egyptian insurance sector. A quantitative approach was used by collecting data from a questionnaire directed to professionals in insurance companies in Egypt. The research founds that the adoption of IFRS 17 significantly improves the quality of financial reporting and increases the creditability and accuracy of financial statements.

## 3. Research Methodology

According to the IFRS17 framework, the conventional perspective across the lifetime of the liabilities is the appropriate approach to quantify the reserve risk to estimate the reserve risk adjustment. There are many approaches to considerate: The standard deviation using the analytical formula-based approaches, a comprehensive predictive distribution is produced using simulation-based approaches.

### Claims Reserving Notation

The triangle of cumulative claims for each line of business can be assumed to be in the following form:

$$\begin{array}{llll} C_{1,0}, & C_{1,1}, & \dots, & C_{1,J} \\ C_{2,0}, & \dots, & C_{2,J-1} & \\ \vdots & & & \\ C_{n,0} & & & \end{array}$$

The run-off triangle has indices $i \in \{`1,2,\dots,n\}$ $and$ $j \in \{0,1,2,\dots,n-i\}$, where i & j are the accident years and the development years, respectively. The cumulative paid claim amounts of accident year i up to development year j are$c_{i,j}$.

(Mack, 1993) Introduced a stochastic methodology for the chain-ladder technique. Beyond the primary objective of the reserving process, which involves estimating the missing lower part of the claims triangle, this approach also facilitates the calculation of the mean and variance of the cumulative claims as follows:

$$E\left[c_{i,j+1} \setminus c_{i,0},\dots,c_{i,j}\right] = \lambda_j c_{i,j} \;\; and \quad Var\left[c_{i,j+1} \setminus c_{i,0},\dots,c_{i,j}\right] = \sigma_j^2 c_{i,j} \tag{5}$$

As only the first two moments of the cumulative claims, rather than the entire distribution, are specified, the model is considered "distribution-free." The variance and the expected value correspond to the previous claims. The unknown parameters $\lambda_j$ $and$ $\sigma_j^2$ are derived by (Mack, 1993), as:

$$\hat{\lambda}_j = \frac{\sum_{i=1}^{n-j-1} w_{i,j} f_{i,j}}{\sum_{i=1}^{n-j-1} w_{i,j}} \tag{6}$$

Where, $w_{i,j} = c_{i,j} \quad and \; f_{i,j} = \frac{c_{i,j+1}}{c_{i,j}}$

And, $$\hat{\sigma}_j^2 = \frac{1}{n-j-2} \sum_{i=1}^{n-j-1} w_{i,j}\left(f_{i,j} - \hat{\lambda}_j\right)^2 \tag{7}$$

The final unknown parameter

$$\hat{\sigma}_{j-1}^2 = \min\left(\hat{\sigma}_{j-3}^2, \hat{\sigma}_{j-2}^2, \hat{\sigma}_{j-2}^4 / \hat{\sigma}_{j-3}^2\right) \tag{8}$$

The development factors $\lambda_j$ are estimated using the standard volume-weighted chain-ladder estimator. Subsequently, the variance estimator $\hat{\sigma}_j^2$ is computed by dividing the residual sum of squares by the degrees of freedom for each development period.

**Bootstrapping reserve variability across the life-time of the liabilities:**

The bootstrapping simulation approach, along with the Mack method, is among the most utilized techniques, as identified by the ASTIN 2016 survey of the main stochastic methods employed by actuaries for reserving. The bootstrapping technique is preferred due to its ease of application and its ability to provide the full distribution of the reserve, rather than just the first two moments offered by the Mack distribution-free approach. (Abdel-naby, 2018)

The bootstrapping approach operates on the principle that once a process is initiated, it can continue independently without further external input. This technique is employed across various disciplines, including business, statistics, biology, and physics, to explore a broad spectrum of processes. In statistics, for instance, bootstrapping involves taking an initial sample and generating numerous additional subsamples from it. In actuarial science, this method is specifically applied to generate a distribution of potential outcomes for each stage in the loss development process. (Shapland, 2016)

The bootstrapping of Mack's model depends on expressing the data as ratios $f$ instead of cumulative claims$c_{i,j}$, result in the following modified equations for the expected value and the variance:

$$E[f_{i,j} \setminus c_{i,0}, \dots, c_{i,j}] = \lambda_j \quad and \quad Var[f_{i,j} \setminus c_{i,0}, \dots, c_{i,j}] = \sigma_j^2 / c_{i,j} \tag{9}$$

Table 1: Mack's parameters per line of business

| | Development years | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | | 2 | | 3 | | 4 | | 5 | |
| Lines of Business | $\hat{\lambda}_j$ | $\hat{\sigma}_j$ | $\hat{\lambda}_j$ | $\hat{\sigma}_j$ | $\hat{\lambda}_j$ | $\hat{\sigma}_j$ | $\hat{\lambda}_j$ | $\hat{\sigma}_j$ | $\hat{\lambda}_j$ | $\hat{\sigma}_j$ |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Fire | 4.694 | 30262.12835 | 1.18 | 3,811 | 1.025 | 342 | 1.002 | 56 | 1.003 | 9 |
| Marine Cargo | 3.11 | 7,999 | 1.24 | 4,333 | 1.01 | 4,140 | 1.00 | 8,493 | 1.02 | 4,140 |
| Inland | 1.98 | 1,429.08 | 1.15 | 305.46 | 1.06 | 254.05 | 1.01 | 55.95 | 1.00 | 12.32 |
| Hull | 3.11 | 15,101.27 | 1.24 | 865.11 | 1.03 | 408.29 | 1.00 | 0.04 | 1.00 | 0.04 |

Source: The researcher based on R

Table 1 showed the estimation of the parameters developed by (Mack, 1993) for the first and second moments estimation on each line of business. The calculation of expected value and standard deviation is the starting point to estimate the estimation error and process error of the Chain ladder reserve.

## Estimating the expected reserve and the reserve risk using simulation based approaches

(England, 2006) provided a predictive distribution for lifetime liabilities consistent with Mack's model by bootstrapping Mack's model as a Generalized Linear Model (GLM). The process of obtaining a predictive model involves a two-step simulation procedure: the first step is for obtaining the parameters, and the second step is for forecasting from the process distribution, which includes both parameter and process uncertainty. To obtain a predictive distribution for a one-year perspective of liabilities, (Merz & Wuthrich, 2008) simulated the Claims Development Result (CDR) consistent with Mack's assumptions. Risk measures, such as Value at Risk (VaR) and Tail Value at Risk (TVaR), can be generated using the simulated predictive distribution as developed by (P.D. England, 2019)

Table 2: : The bootstrapped expected reserve and the bootstrapped standard deviation of ultimate reserve

| Line of Business | Paid | Avg Reserves | Avg Ultimates | Bstrap SD | Bstrap CoV |
|---|---|---|---|---|---|
| Fire | 2,473,440,027 | 914,054,134 | 3,387,494,161 | 612,809,683 | 67.00% |
| Hull | 338,141,644 | 109,983,870 | 448,125,514 | 121,394,493 | 110.40% |
| Inland | 64,443,149 | 19,841,781 | 84,284,930 | 8,386,196 | 42.30% |

| | | | | | |
|---|---|---|---|---|---|
| Marine Cargo | 312,128,848 | 91,618,345 | 403,747,193 | 21,180,980 | 23.10% |

Source: The researcher based on R

Table 2 showed the expected reserve, prediction error (Standard deviation) and the coefficient of variation of bootstrapping Mack's model through 10000 simulations of fire claims triangle.

## Discounting the bootstrapped reserves

Under IFRS 17, the determination of the discount rate for insurance contracts involves considering the time value of money and the specific characteristics of the cash flows associated with those contracts. While IFRS 17 does not prescribe a specific method for estimating the discount rate, the research will use a bottom-up approach to capture the relevant factors. The bottom-up approach is illustrated in the formula below:

*Bottom-Up Discount Rate = Risk-Free Rate + Illiquidity Premium*

The Egyptian Risk-Free Rate is derived from the US Risk Free Rate, adding Egypt Country Risk Premium, which can be approximated 15%

Table 3: Bootstrap Reserves, discounted at 15%

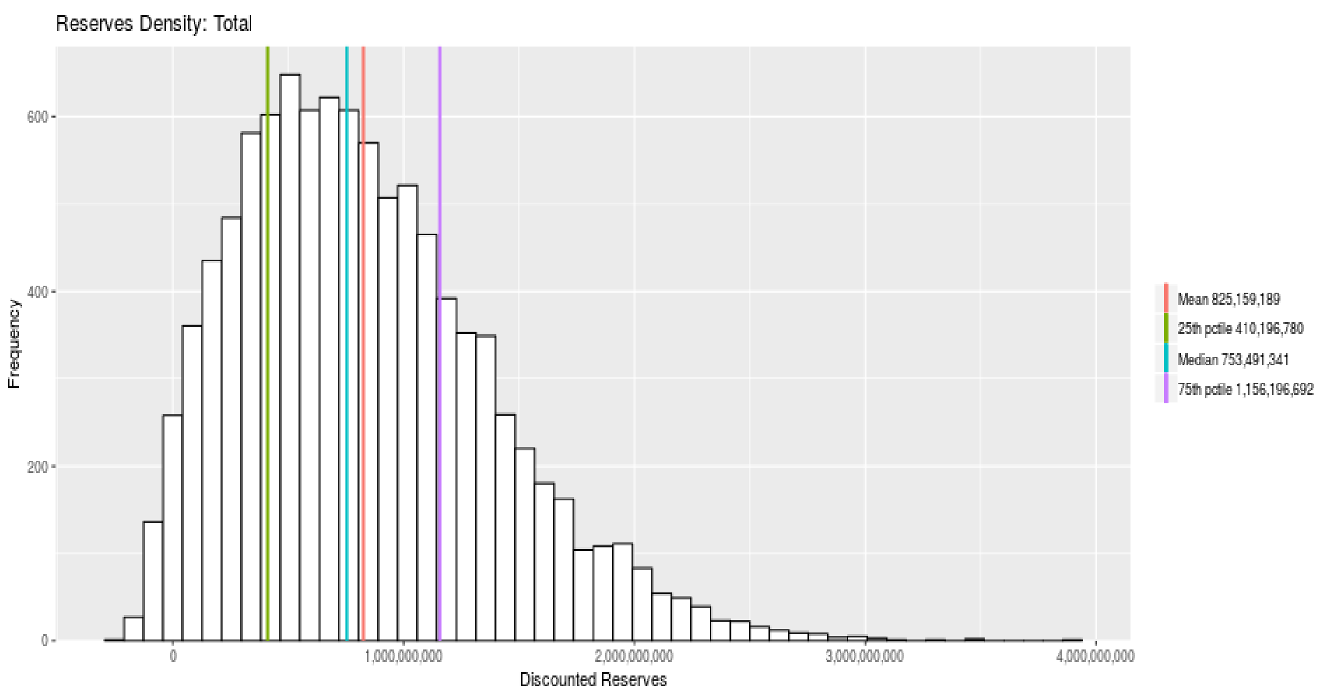
| Line of Business | Avg Reserves | Bstrap SD | Bstrap CoV |
|---|---|---|---|
| Fire | 825,159,189 | 549,100,972 | 66.5% |
| Hull | 98,708,774 | 109,300,571 | 110.7% |
| Inland | 17,505,358 | 7,358,926 | 42.0% |
| Marine Cargo | 80,910,058 | 17,985,788 | 22.2% |

Source: The researcher based on R

Table 3 showed the overall discounted Average reserves, bootstrapped standard deviation and bootstrapped coefficient of variation of implied lines of business. The bootstrapped coefficient of variation is obtained by dividing the bootstrapped standard deviation over discounted Average reserves.

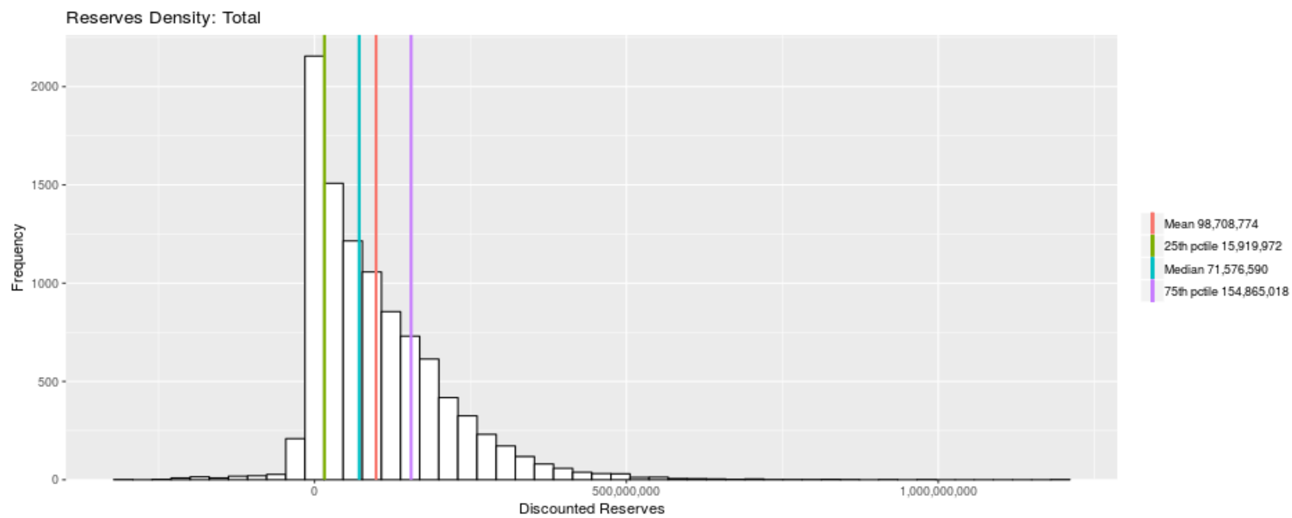
The bootstrap simulation technique has the ability to provide distributions for all future cash flows (not only the reserves). Based on the assumption that the payments are made in the middle of the year, the discounted cash flows are showed in table 3 and described below as a histogram for each line of business.

Figure 1: Fire discounted cash flows histogram



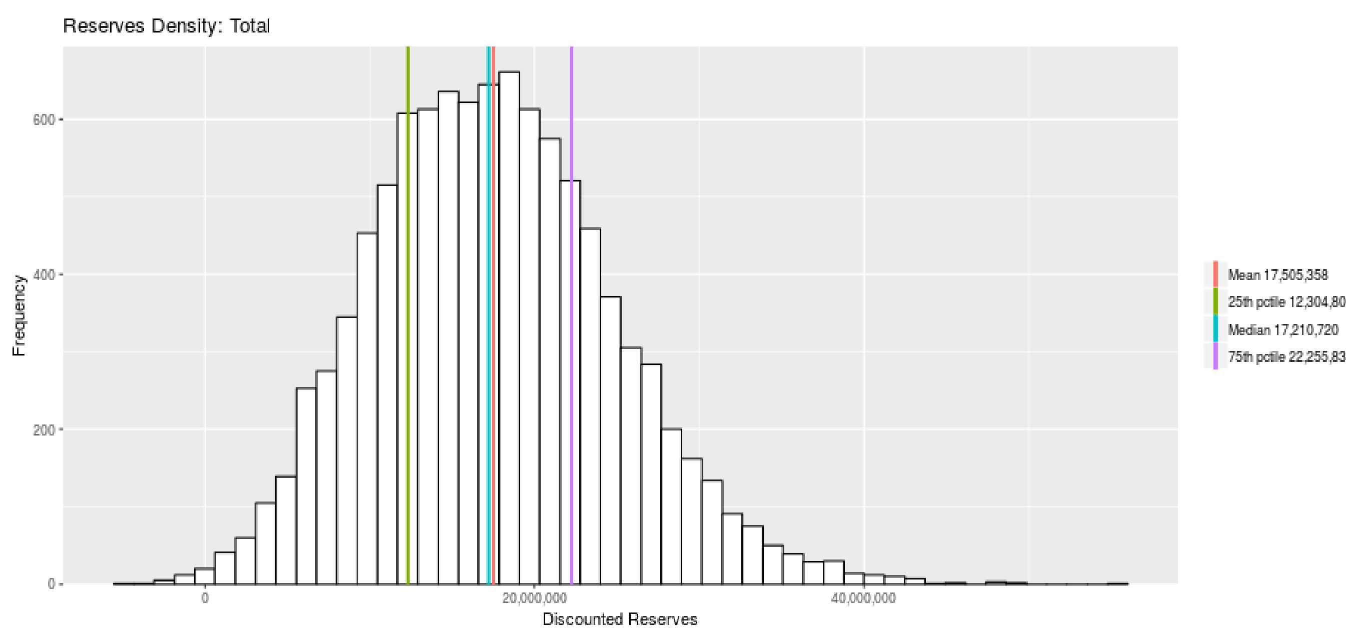

Source: The researcher based on R

**Figure 2: Hull discounted cash flows histogram**



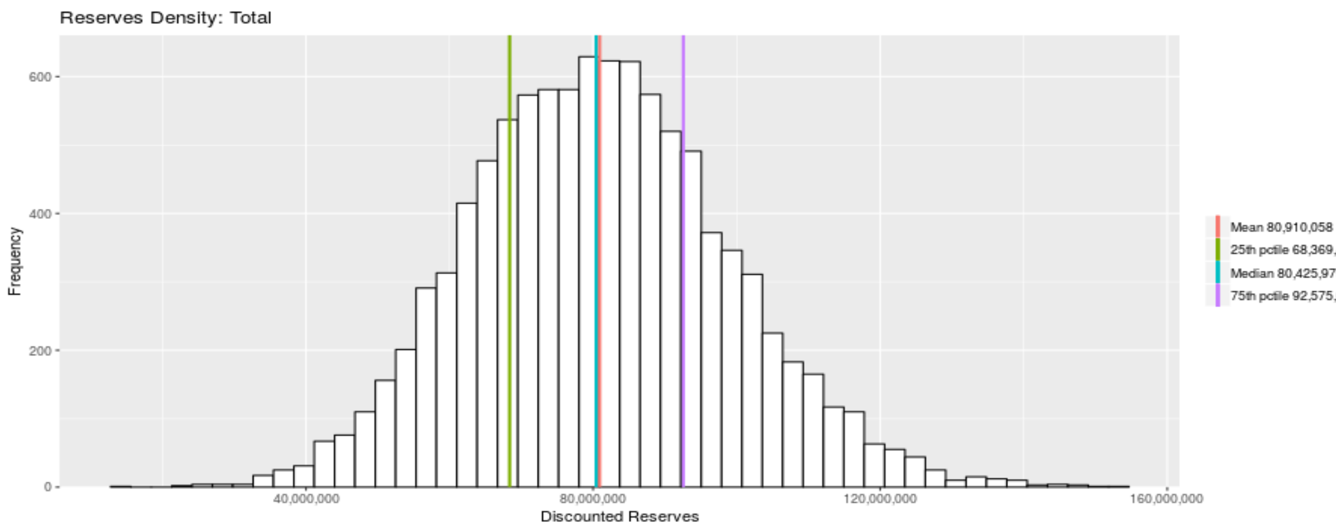

Source: The researcher based on R

**Figure 3: Inland discounted cash flows histogram**




Source: The researcher based on R

Figure 4: Marine Cargo discounted cash flows histogram




Source: The researcher based on R

## Estimating Risk Adjustment using risk measures approach:

The risk adjustment can be estimated by applying the risk measures to the distribution of discounted bootstrapped Mack's model. The VaR may be estimated at confidence level 75% to be consistent with Australian Prudential Regulation Authority. (APRA, 2015)

**Table 4: Fire risk adjustment using risk measures**

| | **Value at Risk** | **Tail Value at Risk** | **Prop. Hazards Transform** |
|---|---|---|---|
| Risk tolerance | 75.00% | 40.00% | 1.85 |
| Risk adjustment | 331,037,503 | 339,129,529 | 386,773,650 |
| Best estimate (disc) | 825,159,189 | 825,159,189 | 825,159,189 |
| Overall | 1,156,196,692 | 1,164,288,718 | 1,211,932,839 |
| Risk adjustment % | 40.12% | 41.10% | 46.87% |

Source: The researcher based on R

Table 4 illustrated the estimation of required risk adjustment for fire LoB using VaR at 75% which resulted in 331,037,503 which represent 40.12%

of discounted reserves. The confidence level (risk tolerance) for TVaR and PHT are selected to be 40% and 1.85 respectively to obtain a risk adjustment equivalent to the risk adjustment using VaR at 75%.

**Table 5: Marine Hull risk adjustment using risk measures approach**

| | **Value at Risk** | **Tail Value at Risk** | **Prop. Hazards Transform** |
|---|---|---|---|
| Risk tolerance | 75.00% | 37.00% | 1.5 |
| Risk adjustment | 56,156,244 | 54,978,580 | 53,029,108 |
| Best estimate (disc) | 98,708,774 | 98,708,774 | 98,708,774 |
| Overall | 154,865,018 | 153,687,353 | 151,737,882 |
| Risk adjustment % | 56.89% | 55.70% | 53.72% |

Source: The researcher based on R

Table 5 illustrated the estimation of required risk adjustment for marine hull LoB using VaR at 75% which resulted in 56,156,244 which represent 56.89% of discounted reserves. The confidence level (risk tolerance) for TVaR and PHT are selected to be 37% and 1.5 respectively to obtain a risk adjustment equivalent to the risk adjustment using VaR at 75%.

**Table 6: Inland risk adjustment using risk measures approach**

| | **Value at Risk** | **Tail Value at Risk** | **Prop. Hazards Transform** |
|---|---|---|---|
| Risk tolerance | 75.00% | 40.00% | 1.85 |
| Risk adjustment | 4,750,475 | 4,675,282 | 4,907,064 |
| Best estimate (disc) | 17,505,358 | 17,505,358 | 17,505,358 |
| Overall | 22,255,834 | 22,180,640 | 22,412,422 |
| Risk adjustment % | 27.14% | 26.71% | 28.03% |

Source: The researcher based on R

Table 6 illustrated the estimation of required risk adjustment for inland LoB using VaR at 75% which resulted in 4,750,475which represent 27.14% of discounted reserves. The confidence level (risk tolerance) for

TVaR and PHT are selected to be 40% and 1.85 respectively to obtain a risk adjustment equivalent to the risk adjustment using VaR at 75%.

Table 7: Marine cargo risk adjustment using risk measures approach

| | **Value at Risk** | **Tail Value at Risk** | **Prop. Hazards Transform** |
|---|---|---|---|
| Risk tolerance | 75.00% | 40.00% | 1.85 |
| Risk adjustment | 11,664,969 | 11,487,415 | 11,511,809 |
| Best estimate (disc) | 80,910,058 | 80,910,058 | 80,910,058 |
| Overall | 92,575,028 | 92,397,474 | 92,421,867 |
| Risk adjustment % | 14.42% | 14.20% | 14.23% |

Source: The researcher based on R

Table 7 illustrated the estimation of required risk adjustment for marine cargo LoB using VaR at 75% which resulted in 11,664,969 which represent 14.42%of discounted reserves. The confidence level (risk tolerance) for TVaR and PHT are selected to be 40% and 1.85 respectively to obtain a risk adjustment equivalent to the risk adjustment using VaR at 75%.

## Risk Adjustment Diversification Benefit Calculation

Besides estimating the risk adjustment using an appropriate technique for each LoB, a key task for the insurer is to identify the type of diversification that is reflected in the insurer’s risk appetite. A copula may be used to estimate the correlation between the LoBs, the non-life correlation matrix of Solvency II Aggregation may be used as a proxy. (Hannibal, 2019)

**Table 8:Correlation matrix between the lines of business**

| LoB | Marine | Fire | Inland | Hull |
|---|---|---|---|---|
| Marine | 1 | 0.25 | 0.25 | 0.25 |
| Fire | 0.25 | 1 | 0.25 | 0.25 |
| Inland | 0.25 | 0.25 | 1 | 0.25 |

| | | | | |
|---|---|---|---|---|
| Hull | 0.25 | 0.25 | 0.25 | 1 |

Source: the researcher based on (CEIOPS, 2008)

The aggregated risk adjustment for the company (under the assumption that the company consists of 4-lines of business) is equal $\sqrt{RA_i \times Corr.Matrix \times RA_i}$ where, $RA_i$ is estimated risk adjustment at 75% VaR for each LoB, as following:

Applying the rule of aggregation based on the previous data resulted in 354,116,630 EGP instead of 403,609,191 EGP if the company just sum the individual risk adjustment without using diversification benefit.

## 4. Conclusions and recommendations:

The research showed that The risk adjustment can be estimated through risk measure (percentile) techniques (Var, TVaR and PHT) that require the risk profile (distribution). the reserve profile can be obtained by a simulation technique (Bootstrapping/Monte Carlo Markov Chain(MCMC)). This research applied three risk measures(VaR, Tvar and PHT). While the Var is considered as the most popular risk measure, the TVar and PHT are coherent risk measures and better at catching skewness/extremes. The discount rate used in this research is approximately 15 % using Bottom-Up approach. Under this research, the highest risk adjustment percentage was for marine hull LoB and the lowest risk adjustment percentage was for marine cargo. These results consistent with the condition of “The risk adjustment for risks with high severity and low frequency is higher than those with low severity and high frequency”. The diversification Benefit to aggregate the risk adjustment using Solvency II correlation matrix as a proxy resulted in decreasing the overall risk adjustment from 403,609,191 EGP to 354,116,630 EGP.

The research recommended that, The Egyptian regulatory authority (FRA) has to set a minimum confidence level for estimated risk adjustment e.g. (75%) and a minimum and maximum discount rate. The dependence between the LoBs has to be considered as the diversification Benefit using a copula or Solvency II correlation matrix as a proxy.

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