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# Modelling Risk Adjustment under IFRS 17

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**DECLARATION**

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Project contains no material previously published or written by another person except where due reference is made in the Research Project itself.



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10/02/2021

This Research Project has been submitted for examination with my approval as the Supervisor.

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## ABSTRACT

The IFRS 17 accounting standard for measuring Insurance profits is effective for periods starting on or after 1 January 2022 and critical to its measurement is the Risk Adjustment factor. The Risk Adjustment measure is the compensation the entity requires for uncertainty about timing and amount of non-financial risks. The issue however is that there is no prescribed calculation to this measure hence entities must derive the calculation that best suits them if they adhere to the IFRS 17 requirements. This study aims to determine the best risk adjustment measure calculation given the Kenyan Insurance market. The study goes into rigorous detail as to the suggested approaches, mainly the discounted cash flow approach and the cost of capital approach and gives an analysis of how to develop the respective models and the outcome of which one worked best in the context of the Kenyan market. Data was obtained from the Insurance Regulatory Authority for the years 2015 – 2019 mainly focused on short term claim statistics. The study established that the Proportional Hazard Transform under the discounted approach would be best suited to the Kenyan market since it explains the significance of the effects of premium on risk. It also satisfies all conditions under the IFRS 17 requirements and is a coherent risk measure.

**Key words:** *IFRS 17, Risk Adjustment, Kenya*

**JEL Code:** *C4, G22*

# Contents

# CHAPTER ONE

# INTRODUCTION

## 1.0 Background of study

Due to the previous inconsistencies in measuring insurance contracts in the past years, the IFRS 17 accounting standard was developed to remedy this flaw. Unlike IFRS 4, an interim standard which allowed insurers to use different accounting policies to measure similar insurance contracts they write in different countries; some practices currently used by insurance companies have evolved in line with circumstances in particular countries hence the need to adopt a new accounting standard. ((2017); IFRS Standards Fact Sheet; IFRS Foundation).

In many cases, features of the accounting models used by the insurance industry are inconsistent with the IFRS Standards applied by other industries in the same country hence limiting comparisons with other industry sectors. IFRS 17 provides consistent principles across the globe for all aspects of accounting for insurance contracts. It removes existing inconsistencies and enables investors, analysts and others to meaningfully compare companies, contracts and industries.

IFRS 17 requires a company to measure insurance contracts using updated estimates and assumptions that reflect the timing of cash flows and any uncertainty relating to insurance contracts such as the estimates of the present value of future cash flows, the risk adjustment for non-financial risk and the contractual service margin. This requirement will provide transparent reporting about a company's financial position and risk.

## 1.1 IFRS 17 Measurement

Within IFRS 17, there are three approaches that have been established to measure a liability depending on duration, the type of liability and whether the contract depends on an underlying item. The liabilities have been categorized into two: Liability for Remaining coverage (LRC) which represents the unearned portion of risk from insurance contracts which are in force and Liability for Incurred Claims (LIC) which represent insurance events that already occurred but the claims have not been reported or have not been fully settled.

The three models established are the General measurement model, the Premium Allocation Approach (PAA) and the Variable Fee Approach (VFA). The Premium Allocation Approach is often used to simplify short term contracts while the Variable fee approach is used where policy cash flows are linked to underlying investments such as unit linked contracts. The general measurement model is the default model and upon initial recognition, it is composed of the sum of the fulfillment cash flow (FCF) and the contractual service margin (CSM) which reflects the unearned profit the entity is recognized as the firm provides services in the future. The fulfillment cash flow is made up of the estimate of future cash flows, an adjustment to reflect time value of money and financial risk related to the future cash flows (a discounting factor) and finally the risk adjustment measure which considers the uncertainty in the amount and timing of cashflows arising from non-financial risk. (IASB 2017(b))

## 1.2 The Risk Adjustment Measure

The influential risk adjustment measure under IFRS 17 is defined as "the compensation an entity requires for bearing the uncertainty about the amount and timing of the cash flows that arises from non-financial risk as the entity fulfills insurance contracts". It measures the negative value or cost an entity places on the uncertainty and variability inherent on insurance cash flows. It is noteworthy however that IFRS 17 does not prescribe a specific measurement method for calculating this risk adjustment and as such entities are expected to develop their own internal models depending on the entity's risk appetite.

The objective of the risk adjustment measure is to provide a quantitative assessment of risk based on the entity's risk preferences. The entity considers the following elements when calculating the risk adjustment: Risk appetite, the key drivers of risk, the complexity of the models in use and the ability to explain and quantify the risk adjustment in the context of financial statements. (IAA 2018).

The risk adjustment measure is necessary as it shows how profit from insurance contracts emerges over time and how it should be reported. It also reflects the degree of diversification benefit the entity includes when determining the compensation required for bearing that risk. With this necessity, there are accounting requirements for calculation, disclosure and presentation of the risk adjustment in order to ensure consistency among firms. These requirements will be addressed in this and subsequent chapters.

The requirements necessary for risk adjustment calculation are: The risks with low frequency and high severity result in higher risk adjustments for non-financial risk than risk with high frequency. For similar risks, contracts with a longer duration result in higher risk adjustment for non-financial risk than contracts with a shorter duration. Risks with a wider probability distribution result in higher risk adjustment for non-financial risk than risks with a narrower distribution. The less is known about a current estimate and its trend, the higher is the risk adjustment for non-financial risks and finally when emerging experience reduces uncertainty about the amount and timing of cash flows, risk adjustment for non-financial risk decreases and vice versa.

The disclosure requirements are that the entity should disclose the equivalent confidence level of the calculated IFRS 17 risk adjustment. The disclosures must also include a reconciliation from the opening to the closing balances of risk adjustment. Other risk adjustment requirements are if similarities exist between the IFRS 17 risk adjustment and existing reporting metrics, the insurance company is expected to be consistent with existing measures or be able to justify any differences.

The scope of the risks accounted for by the risk adjustment is only non-financial risks. Some of the risks included in the modelling claim amount risk, inflation risk, lapse risk, surrender risk and other policyholder actions. However, the risks that were excluded from this framework are operational risk, asset liability mismatch risk and the price or credit on underlying variables.

## 1.3 The Kenyan Insurance Sector

The Insurance industry in Kenya is one that is slowly but steadily growing, as at 2018 there was a growth of 3.5% from the previous year making the gross premium income KES 216.2 billion. For that year, the total long term insurance business claims and benefits increased by 9.3% to KES 54.06 billion, the highest share being from pensions while the general insurance sector also saw an increase of 0.71% in claims getting it to KES 56.93 Billion the highest percentage of claims originating from medical and motor classes of insurance.

According to the Insurance Regulatory Authority (IRA), the model currently being used to recognize profits from insurance contracts is the risk based capital model also known as the capital adequacy framework which entails the capital requirement ratio to be the ratio between the capital required and the minimum capital required.

### 1.4 Modelling Practices for the Risk Adjustment measure

The main approaches that have been suggested for Risk Adjustment measurement under IFRS 17 are the cost of capital approach and the discounted approach which is further divided into three sub-categories namely the Value at Risk approach, the Tail Value at Risk approach and the Wang's Proportional Hazards transform.

The cost of capital methodology assesses the cost of holding capital sufficient to cover the relevant risks over the lifetime of the business. It requires judgment to determine the appropriate level of capital in the future and the cost of capital rate. The appropriate level of capital is prescribed as that required to cover all non-market risks. Its advantage is that it could be used as a useful benchmarking tool across all firms however its downfall is that it does not reflect how a firm wishes to express its risk appetite.

Under the discounted approach, the value at risk methodology is from a single simulation. It could be subject to considerable volatility (especially at higher percentiles). This methodology requires an entity to calculate the discounted value of the best estimate future cash flows under a range of different scenarios to produce a risk distribution. The entity then decides on the confidence level that would be appropriate for their nature of business. Its advantage is that it is very well understand however it does not capture skewness.

The tail value at risk method uses equal weights above a given percentile level. It also obeys the sub-additivity property, so is potentially useful for allocations to lower levels. This measure is also calculated with reference to a particular confidence level, however, the total value at risk is the expected value above that confidence level. It captures skewness better than the value at risk method but it is less well understood.

The proportional hazard transform uses increasing weights across all simulations and is better at catching skewness. It has a range from the mean to the maximum simulated value. This method is a coherent risk measure, and as such obeys the sub-additivity property, so is potentially useful for allocations to lower levels. Despite this, it may be difficult to explain to non-actuaries.

## 1.5 Problem Statement

The risk adjustment measure plays a central role on how entities will recognize profits under the IFRS 17 accounting standard. It is also a crucial measure because the base of its calculation is solely dependent on an entity's risk appetite and preferences. Despite its importance, methods it is yet to be understood which methods work best in which environments and companies.

Under the Insurance sector, there was a study used to develop risk adjustment rates using demographic factors and diagnostic information alongside development of risk adjusted capitation rates for the National Hospital Insurance Fund (NHIF). (Mungai, Joan Wanja (2015), Diagnosis based Risk Adjustment of Capitation Rates, The case of National Hospital Insurance Fund, Strathmore University) This study was well developed however the methods implemented in the study were not similar to the ones suggested in the IFRS 17 Framework. This research aims to highlight which of the suggested methods of measuring risk adjustments under IFRS 17 would be best suited for a firm in the Kenyan Insurance industry.

This research will be highly relevant as the adoption of the IFRS 17 accounting standard in Kenya has been proposed to be implemented for periods beginning on or after January 2022. This adoption is expected to bring an extreme change in the reporting of insurance contracts. In addition, insurers will be forced to upgrade their reporting systems which will see actuaries and accountants coming together to help in the adoption of the new processes.

It is in this light that this study aims to compare and further develop the risk adjustment models stated above for the Kenyan market. In addition, the study seeks to determine the best risk adjustment model to be used in the Kenyan context.

## 1.6 Research Objectives

I. To determine the most suitable specification for risk adjustment models in the Kenyan Insurance market.

## 1.7 Research Questions

I. What is the best approach in the specification of risk adjustment?

## 1.8 Significance of Study

By developing an efficient model, this study offered a suitable method for estimation of the risk adjustments to be accounted for under insurance contracts in Kenya. Firms that use the model prescribed by this study may have a less time consuming and hence less expensive way to estimate the risk adjustment. This played a role in assisting insurance companies to implement IFRS 17 requirements in their financial reporting in the years to come.

# CHAPTER TWO

# 2 LITERATURE REVIEW

## 2.1 IFRS 17 and the Risk Adjustment framework

The risk-adjustment measure under IFRS 17 is defined as "the compensation an entity requires for bearing the uncertainty about the amount and timing of the cash flows that arises from non-financial risk as the entity fulfills insurance contracts. It shall not reflect the risks that do not arise from the insurance contracts, such as general operational risk." Therefore, the risks that was included are: Claims, benefits, services, expenses associated directly with fulfilling the contracts, premium and fees receivable.

The risk adjustment can be understood as the price assigned by the insurer for bearing the non-financial risks associated with the portfolio of insurance contracts, more specifically, the risks that arise from unfavorable outcomes on a long-term horizon. This assigned price has to meet the objective and characteristics described.

"The objective of a risk adjustment is to provide a quantitative assessment of risk based on the entity's risk preferences". To meet the objective, the following elements mentioned in IAA (2018) will be considered in developing the adjustment: Risk preferences, key drivers of risk, the complexity of the probability or stochastic models and the ability to explain and quantify the risk adjustments in the context of financial statements.

## 2.2 Theoretical Approach

From previous work done, it is noteworthy that the formula to be used is not just made once and left alone. There was a need to evaluate and periodically adjust and improve the risk-adjusted subsidy formula over time. We examine the specific risk factors and models that can be used for calculating the best estimate of acceptable costs. We begin with a discussion of criteria that can be used for assessing risk adjustment models, and apply these criteria to issues related to designing, evaluating, and choosing a model. Specifically, we consider: criteria for selecting a risk adjustment model; choice of prediction period; choice of explanatory variables to use for risk adjustment; selection of a functional form; and use of summary statistics to assess and compare alternatives.

(Wynand P.M.M. Van De Ven. (2000) Risk adjustments in competitive healthplan Markets, Handbook of heath economics.)

### 2.2.1 The Approach to choosing an efficient Risk Adjustment model

The criteria to be chosen from are grouped into three broad categories which could be mutually related. The categories are; Appropriateness of incentives, the model being developed should be driven with not only correct but also appropriate incentives. This is the most important category. Among the criteria, there is also feasibility; the feasibility of risk adjustment models imposes constraints on the key tradeoff between efficiency and fairness discussed in previous sections. Although a perfect risk adjustment model might be able to eliminate this tradeoff, such a model might not be feasible to implement. It is also important to note that large samples exist on which risk models are developed and parametized prior to implementation. This weakness is serious for survey-based predictors. Finally, there is fairness, in that some countries do put an emphasis on the fairness aspect of the model however other countries do not. Fairness includes variables such as lifestyles, tastes, religion etc. a risk adjustment system was often be considered fairer if it predicts a larger proportion of the variation in spending. Having put all the above categories into consideration, let us now consider the methodology that has been used while developing risk-adjustment models.

## 2.3 Practical Approach

From a study conducted in 2012, risk scores were introduced as a point estimate. The risk score is made up of factors such as turnover, eligibility, lag, data quality etc. The developer may choose what factors to incorporate into their risk score measure. In risk adjustment, a very common practice is to calculate group average risk scores and allocate budgets based on the relativities of the average scores. When using samples to infer the relative risk of groups, the following question arises. Are the differences in group average risk scores statistically significant to justify the movement in the budget?

Well to answer the above question, the researcher utilized the t-statistic in order to compute the minimum difference in risk score needed for statistical significance at a desired level of significance. The calculation for the required minimum difference for statistical significance depends upon the size of groups that are being compared, and the sample variance of risk scores within those groups. The researcher still used the t-test to determine whether two different risk scores are statistically different.

However, even this test may mislead in cases where the population sizes and variances are very different. Risk scores at an individual level are not normally distributed. However, given a large enough sample/group size, the central limit theorem implies that the average risk scores will be roughly normally distributed. In reality, no data is ever perfectly normally distributed or has exactly equal variance therefore all practical applications of the t-test should be qualified as approximate t-tests.

As discussed previously, risk adjustment models use large, representative populations therefore when implemented there should be an accuracy test. The researcher utilized confidence intervals to determine the accuracy and suitability of the data. (Syed Muzayan Mehmud. And Rong Yi. (2012) Uncertainty in Risk Adjustments, Society of Actuaries health selection)

## 2.4 Risk Adjustment Models

### 2.4.1 One-year estimation uncertainty associated with using credibility-based loss reserving methods.

The claim development can be described by the models of Bühlmann-Straub or Hesselager-Witting._Having found a formula, it seems natural to minimize the one-year estimation uncertainty in the same way as one can minimize the ultimate uncertainty, i.e. to minimize the MSEP._It turns out that minimization of the one-year estimation uncertainty leads to unreasonable and unsightly results. This puts into question the sanity of the concept of one-year estimation.

The Buhlmann-Straub (Bühlmann and Straub 1970) model combines the notion of a known risk exposure with the notion of an à prior unknown claim rate. Bühlmann and Straub model the unobserved claim rate as a random variable and derive an optimal credibility estimator to estimate the claim rate in the light of emerging claim experience.

The Hesselager- Witting (Hesselager and Witting 1988) model was an extension of the Buhlmann model to comprise not only an à priori unknown claim rate, but also an à priori unknown claim development pattern. The result was that the credibility assigned to the claim experience in the optimal credibility estimator, decreases when the claim development pattern is random. The Hesselager-Witting model includes the Bühlmann-Straub model as a limiting case, in which the claim development pattern is fixed.

### 2.4.2 Collective Risk Model

A common practice in the insurance industry is to use the collective risk model which provides a way to understand the aggregate loss as the sum of the individual claims.

Following the notation from Klugman et al. (2008), let S be the random variable which represents the aggregate loss of a random number of claims N, of independent and identically

distributed random variables $Xi \; where \; i = 1,2, \dots . n$. In the insurance industry, Nis known as the frequency component and Xi as the severity. Then, S has the following additive representation;

$$S = 0; N = 0; X1 + X2 + \cdots + Xn \quad \text{When N} > 0$$

The collective risk model has the following independence assumption:

Conditionally on $N = n$, N and the i.i.d. sequence $Xi, i = 1,2 \dots, n$ are independent.

N has to be a discrete count random variable and in the insurance context X follows a positive continuous random variable.

More of the research work done presents the risk adjustment as it should be estimated under IFRS 17. IFRS 17 states that, "An entity shall estimate the expected value (ie the probability weighted mean) of the full range of possible outcomes", plus "a risk adjustment for non-financial risk."

The risk adjustment for non-financial risk for insurance contracts measures the compensation that the entity would require to make the entity indifferent between fulfilling a liability that has a range of possible outcomes arising from non-financial risk and fulfilling a liability that was generate fixed cash flows with the same expected present value as the insurance contracts.

## 2.5 Summary of The Literature Review

A thorough review of the literature showed major similarities especially at the base level however when it came to clear and concise methods, the most recent papers were more developed and provided efficient direction while elaborating the confidence level as well as the conditional tail expectation.

Risk adjustment is a widely researched topic and from the different approaches given, risk adjustment techniques have come a long way over the past two decades, increasing both in its predictive power and in its sensitivity to creating appropriate incentives. However, there is room for expansion in this field. There is reason to believe that episode-based models and models that make better use of the timing of new information generated during the year also hold out promise of improving the predictive power of risk adjustment models. There is also promise in models that predict individual level expenditures on specific services instead of in aggregate terms.

However, there is gray area to be discussed and that is reinsurance. Reinsurance contracts held must be recognized, measured and disclosed separately from the gross figures. Moreover, the cash flow distribution must reflect the risk of non-performance by the reinsurer. Therefore, applying gross to net ratio for the whole reinsurance structure (proportional and non-proportional) seems inaccurate. Then, estimating risk relating to reinsurance contracts will be complex without the use of a simulated approach. (Jignesh Mistry, Rob Walton (2019); Practical challenges of implementing the IFRS 17 Risk Adjustment; Institute and Faculty of Actuaries)

Insurance companies must think about the contractual service margin as well. From a reinsurance contract point of view, it can cover insurance policies that have not been signed yet. At the same time, from a policy point of view, some future claims related to current policies would be covered by reinsurance treaties that have not been signed yet. There is simply mismatch between gross and net of reinsurance results because of the underlying measurement models and constraints brought by the standard. ((April 2018); Paper 08-03; EFRAG Board Meeting)

# 3 METHODOLOGY

## 3.1 Introduction

From IFRS 17, there is no specific method prescribed in the risk adjustment calculation however a confidence level associated with the risk adjustment must be provided in all cases. There are four different suggested approaches that can be used in the calculation. This research seeks to determine which of these approaches is best suited for the Kenyan Insurance market.

## 3.2 Research Design

The study adopts an exploratory research design. Exploratory research is the process of investigating a problem that has not been studied or thoroughly investigated in the past as is the case for Risk Adjustment. This study will involve three stages as: (1) Obtaining the risk adjustment using different approaches and (2) Determining the confidence level.

## 3.3 Obtaining the risk adjustment using different approaches

### 3.3.1 Discounted Approach

Under this approach, the confidence level is included in the calculation. Also, the methods that fall under this approach should satisfy the four requirements of coherent risk measures which are translation-invariance, sub-additivity, homogeneity and monotonicity. The following methods constitute the discounted approach:

### 3.3.2 Value at Risk Approach

The Value at Risk is a risk measure that is normally obtained from a single simulation. It represents the minimum loss incurred within a given time horizon if one of the (1-α) % worst case scenarios occurs. Consider the random variable X, then;

$$VaR(X) = \inf\{x \in \mathbb{R} | P[X \leq x| \geq \alpha\}$$

Value at Risk is measured by assessing the amount of potential loss, the confidence level and the time frame. It has a range from the minimum to the maximum simulated values. This approach requires an entity to calculate the discounted value of the best estimate future cash flows under a range of different scenarios to produce a risk distribution. From this the entity then decides on the confidence level that would be appropriate for their nature of business. The risk adjustment is then set to be equal to the value at risk at that confidence level less the discounted value of the best estimate future cash flows.

There are three different methods of calculating Value at Risk. The first method is the historical method which re-organizes actual historical premiums, putting them in order from worst to best. It then assumes that history repeated itself, from a risk perspective. The second method is the Variance covariance method which assumes that premiums are normally distributed. In other words, it requires that we estimate only two factors - an expected (or average) return and a standard deviation which allow us to plot a normal distribution curve. The third method is the Monte-Carlo simulation developing a model for future premiums and running multiple hypothetical trials through the model. It randomly generates trials, but by itself does not tell us anything about the underlying methodology.

An entity may apply their existing VaR techniques in the calculation of RA. However, there are some noteworthy differences such as the risk profile; the economic capital can include all risks faced by the entity, whereas the RA is only required for non-financial risk. The second difference is the time horizon; the economic capital tends to be calculated over a one-year time horizon, whereas the time horizon for the calculation of the confidence level of the RA would reflect all cash flows within the contract boundaries ie a lifetime horizon. The entity could determine the level of the RA based on one-year shocks, but the associated confidence level would be calibrated against a lifetime horizon. The last difference is comparability in that the economic capital is often calibrated at a higher percentile over a one-year time horizon however the confidence level of the RA would generally reflect a lower percentile over a longer time horizon. As such, the two amounts may not be directly comparable.

The VaR measure is quite easy to understand and to carry out given the data, despite this it has major shortcomings as a measure of risk. It fails to satisfy the sub-additivity property, by this it implies that the risk adjustment calculated for a higher confidence level might be too high therefore making it an incoherent measure of risk. This measure also ignores all results higher than the chosen confidence level which might be a problem especially if the distribution has heavy tails.

### 3.3.3 Tail Value at Risk/Conditional Tail Expectation

As the name implies, the Tail Value at Risk is closely related to the Value at Risk approach, it is defined as the expected loss of the worst (1-α) % cases and thus, its equation is related to the VaR;

$$TVaR(X) = \frac{1}{1-\alpha} \int_0^1 VaR\ (X)du$$

This measure is quite straightforward to calculate as it takes into account the extreme values in the tail because it takes into account the expected value. It has a range from the mean to the maximum simulated value as the percentile level changes. It better fits distributions with heavier tails. If an insurer applies the Tail Value at Risk approach on actual data, they can derive the Tail value at risk directly from the data by calculating the average of the (1-α) % highest values.

This measure is also calculated with reference to a particular confidence level, however, the total value at risk is the expected value above that confidence level. For example, if a 99.5th confidence level is chosen, the total value at risk would be equal to the expected value given an extreme tail event. This method may be restrictive for entities that do not use stochastic techniques as a full risk distribution would be required in order to calculate the total value at risk. Firms could calculate CTE using an assumed standard distribution however, it would be necessary to give a justification for the use of the chosen standard distribution.

The TVaR measure is a coherent measure of risk and it addresses some of the weaknesses of the VaR approach however it does have some of its shortcomings. It might not be accurate because higher more unlikely values are often not part of a random data set which could give a distorted result. From a consistency point of view, TVaR may be less desired as it is driven by the shape of the tail which could be more volatile hence less predictable.

### 3.3.4 Proportional Hazard Transform

This is a proposed premium principle by Wang, 1995. Just as the two previous risk measures, it does require a risk distribution. For a risk X, the risk adjusted premium is the mean of the transformed distribution, in that for a non-negative loss random variable X, with a survival function S(X) such that $Sx(u) = \Pr(X > u) = 1 - \Pr(X \leq u)$, then $E[X] = \int_0^{\infty} Sx\, du$. The Proportional Hazard mean with parameter p is given by Hp where:

$$Hp = \int_0^{\infty} [Sx\,(u)]^{\wedge}\, {}^{1}/_{p} \; du \qquad \text{for } p \geq 1$$

The principle quite resembles risk neutral valuation in option pricing but it differs from utility theory. Despite this, it still preserves the ordering of risks as used in utility theory. Some of the characteristics of this measure is that it uses increasing weights across all simulations, it is also better at catching skewness as compared to the previous two methods and it has a range from the mean to the maximum simulated value. It satisfies all the properties of risk measures hence making it a coherent measure of risk.

## 3.4 Cost of Capital Approach

This approach assesses the cost of holding capital sufficient to cover risks over the lifetime of the business. It is more complex as compared to the other three as it requires additional variables, assumptions and sensitivities. The appropriate level of capital is prescribed as that sufficient to cover non-hedgeable risks using solvency 2 approach of applying adverse stress scenarios. It is also important to note that this method also requires judgement to determine the appropriate capital level in the future as well as the cost of capital rate.

The risk adjustment under the cost of capital approach is calculated as the discounted value of the future risk capital considered appropriate to hold in respect of non-financial risks multiplied by the entity's internal cost of capital rate. The discount rate used depend on the asset selection for the risk capital and it should only reflect the return that an entity can reasonably expect to earn. The calculation is described by the following formula:

$$RA = \Sigma t \, \frac{Rt \; x \; Ct}{(1-dt)^{\wedge}t}$$

Under this approach, any capital model can be used if it is consistent with the entity's views regarding compensation. Despite this possibility of choice, the capital requirement should be adjusted to satisfy the following considerations: Removal of the capital component(s) related to risks other than the non-financial risks in scope of the risk adjustment. Diversification, if not specifically addressed in the capital model being used. Consideration of the various risk-sharing mechanisms such as reinsurance reflected in the estimates of future cash flows and the inclusion of a non-financial capital component for risks without explicit non-financial capital components in the capital model, if significant. The company also needs to determine a suitable allocation method for this capital requirement.

As with the other methods, this method also has its advantages and its shortcomings. Some of the benefits of the Cost of capital approach is that it offers familiarity and it could be used as benchmarking tool across different firms in the insurance industry. This measure however fails to reflect how a firm would wish to express risk appetites. It also raises questions to its application because despite it being a coherent risk measure, it does not disclose the confidence level which is one of the main disclosure requirements under IFRS 17.

## 3.5 Determining the Confidence Level

Under IFRS 17 disclosure requirements, a company must disclose the equivalent confidence level regardless of the approach being implemented. This might be easier for firms that are using a stochastic model however for firms without this capability, an assumption will have to be made with respect to the shape of the risk distribution of insurance liabilities.

The implemented confidence level should be derived from results of the firm's used technique. It can be calculated in the following way: Derive and assume a distribution and a standard deviation for the future cash flows. The mean of the distribution will be $\gamma$. Denote the probability density function of this distribution with g(x). The derived confidence level will be the percentage of the distribution that lies to the left of ($\gamma$ + Risk Adjustment). This means that the confidence level can be calculated using:

$$Cd = \int_{-\infty}^{\gamma+RA} g(x)\, dx$$

## 3.6 Data

The data that was used was extracted from General Insurance (short term) claim settlement statistics from 2015 to 2019 from the Insurance Regulatory Authority.

# CHAPTER FOUR

# 4 ANALYSIS AND INTERPRETATION OF RESULTS

## 4.1 Introduction

This chapter outlines the analysis of the data and interpretation of the financings based on the objectives. The study was to determine the most suitable specification for risk adjustment models in the Kenyan Insurance market and to develop the model in terms of the Kenyan market. The data was analyzed using excel and gretl software. The Discounted Approach of modelling was adopted. The results were displayed and interpreted as shown in the subsections below.

## 4.2 Data summary

The data was acquired online form General Insurance (short term) claim settlement statistics from 2015 to 2019 from the Insurance Regulatory Authority. Total data for premium paid by the clients and net profits in the insurance companies in Kenya was used to provide information on medical claim and motor claim for insurance companies. Data was cleaning and organized in excel. Tables and graphs were used to presented results.

### 4.2.1 Data presentation

The total premium received by the insurance companies in Kenya was computed and presented in the figure 4.1 as shown below.

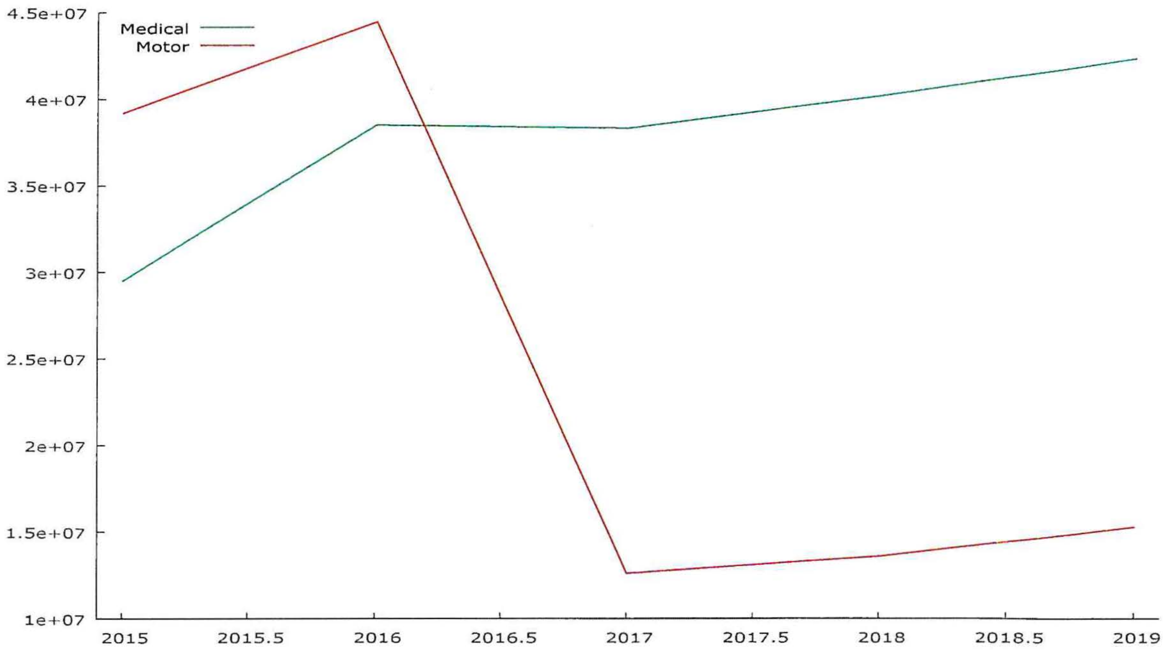


Figure 4.1 Medical and Motor premium.

From figure 4.1 the motor premium was high about KES 45 Million during the year 2016 while the lowest being slightly below KES 15 Million in 2017.On medical, the premium received was slightly below Ksh.40 Million in 2016 and lowest in 2015 about KES 30 Million.

### 4.2.2 Normality test

The normality test was conducted using Shapiro-Wilk W test. The data for premium on medical claim and motor vehicles was tested for normality before generating model to measure risk. The data for premium of medical claim was subjected for normality test and the results are indicated in the following table:

Table 4.1 Normality test summary

| | **Test for Normality (Medical)** | **Test for Normality (Motor Vehicle)** |
|---|---|---|
| Shapiro – Wilk W | 0.840827 | 0.78037 |
| p value | 0.167221 | 0.0555254 |

This led to acceptance of the null hypothesis that the data is normally distributed since the p-value>0.05. Thus the data used based on medical & motor vehicle claims for the years 2015 to 2019 was normally distributed.

### 4.2.3 Summary Statistics

The data was summarized using mean, standard deviation and coefficient of variation. The results were as shown in the table below:

Table 4.2 Summary Statistics

| | **Medical claim** | **Motor vehicle** |
|---|---|---|
| Mean | 25,052,767 | 37,782,676 |
| Standard Deviation | 4,894,947 | 15,353,999 |
| Coefficient of Variation | 0.12956 | 0.61763 |

From table 4.1, the average premium of medical claims for the 2015 to 2019 was KES 25 Million while for motor vehicle claims was KES 37 Million. This indicates that average premium for motor vehicle was more than that of medical claim. The coefficient of variation under the medical claims was 0.61763 which was high compared to that of motor vehicle which was about 0. 12956. This indicates that the distribution of premium for medical claims had differed up to 61.763% from 2015 to 2019 while that for the motor vehicle was 12.956%. This indicates that motor vehicle premium deviated slightly from 2015 to 2019 compared to that of the medical claim premium.

## 4.3 Value at Risk Model

The Value at Risk was calculated from premiums of both the medical and motor vehicle claims for the data from 2015 to 2019. It was calculated as a measure a risk that was obtained from a single simulation. The results were calculated and presented as shown in the table:

Table 4.3 Value at Risk

| | Medical Claim | Motor Vehicle |
|---|---|---|
| Portfolio Value | 188,913,378 | 125,263,833 |
| Expected Volatility | 4,894,947 | 15,353,999 |
| Time (in years) | 1 | 1 |
| Confidence Interval | 0.99 | 0.99 |
| Stress event | 2.33 | 2.33 |
| VaR | 409 Trillion | 851 Trillion |

From table 4.3 it indicates that medical claim premium had a value at risk of about KES 409 Trillion while the motor vehicle claim premium had a value at risk of about 851 Trillion and they both represent the minimum loss incurred within a given time horizon if one of the 99 % confidence interval worst case scenarios occurs during the period between 2015 and 2019.

## 4.4 Conditional Tail Expectation

The Conditional Tail Expectation was calculated from premium for both medical claim and motor vehicle for the data from 2015 to 2019. It was calculating to measure the expected loss of the worst 99 % cases obtained from a single simulation for both medical and motor vehicles. The results were calculated and presented as shown in the table below:

Table 4.4 Conditional Tail Expectation

| | Medical Claim | Motor Vehicle |
|---|---|---|
| Mean | 37,782,676 | 25,052,767 |
| Standard Deviation | 4,894,947 | 15,353,999 |
| z | 72366.55424 | 72366.55424 |
| Conditional VaR | 3.1 Trillion | 1.8 Trillion |

From table 4.4, it indicates that medical claim and motor vehicle claim premium respectively had a conditional value at risk of about KES 3.1 Trillion and KES 1.8 Trillion which represents the minimum loss incurred within a given time horizon if one of the 99 % confidence interval worst case scenarios occurs during the period between 2015 and 2019.

## 4.5 Proportional Hazard Transform

The proportional hazard transformation was calculated from premium for both medical claim and motor vehicle for the data from 2015 to 2019. Just as the two previous risk measures, it does require a risk distribution. The Proportional Hazard mean was calculated using gretl software and run under 20 iterations and the results were presented in the table below:

Table 4.5: Model 1: Logistic regression, using observations 2015-2019 (T = 5)

Dependent variable: L
Standard errors based on Hessian

| | *Coefficient* | *Std. Error* | *z* | *Slope** |
|---|---|---|---|---|
| const | −2.84668 | 10.4688 | −0.2719 | |
| Medical | 3.84292e-08 | 2.72348e-07 | 0.1411 | 6.11761e-09 |

| | | | |
|---|---|---|---|
| Mean dependent var | 0.200000 | S.D. dependent var | 0.447214 |
| McFadden R-squared | 0.004169 | Adjusted R-squared | -0.795188 |
| Log-likelihood | −2.491582 | Akaike criterion | 8.983165 |

| | | | |
|---|---|---|---|
| Schwarz criterion | 8.202041 | Hannan-Quinn | 6.886705 |

| | |
|---|---|
| Number of cases 'correctly predicted' | 4(80.0%) |
| f(beta'x) at mean of independent vars | 0.447 |
| Likelihood ratio test: Chi-square (1) | 0.0208595 [0.8852] |

Table 4.6: Model 1: Logistic regression, using observations 2015-2019 (T = 5)

Dependent variable: L

Standard errors based on Hessian

| | *Coefficient* | *Std. Error* | *z* | *Slope** |
|---|---|---|---|---|
| const | −1.42359 | 5.4688 | −0.3124 | |
| Motor | 2.424562e-08 | 1.72348e-07 | 0.1411 | 5.11761e-09 |

| | | | |
|---|---|---|---|
| Mean dependent var | 0.100000 | S.D. dependent var | 0.234156 |
| McFadden R-squared | 0.004169 | Adjusted R-squared | -0.795188 |
| Log-likelihood | −1.491582 | Akaike criterion | 7.983165 |
| Schwarz criterion | 7.202041 | Hannan-Quinn | 4.886705 |

| | |
|---|---|
| Number of cases 'correctly predicted' | 4(80.0%) |
| f(beta'x) at mean of independent vars | 0.447 |
| Likelihood ratio test: Chi-square (1) | 0.0189078 [0.66752] |

From tables 4.5 and 4.6, these models indicate that the higher the premium of medical claim the higher the risk. The effect of the premium on the risk is also significant at $p<0.05$. This means that the equivalent hypothesis to the objected is it was to be tested then there is possibility of rejecting null hypothesis that premium of medical and motor vehicle do not have a significant impact on the risks.

## 4.6 Cost of Capital Approach

The cost of capital Approach was computed based on medical claim and motor premium. The results were displayed as shown in the following tables:

Table 4.7 Cost of Capital (Medical)

| | | Medical | | |
|---|---|---|---|---|
| **Year** | **Cost** | **Rate** | **Deviation** | **RA** |
| 2015 | 29,516,467 | 19,929,257 | -9,587,210 | 61,356,870 |
| 2016 | 38,515,454 | 38,515,454 | 0 | 38,515,454 |
| 2017 | 38,337,371 | 236,752 | -38,100,619 | 238,223 |
| 2018 | 40,195,984 | -1,191,497 | -41,387,481 | -1,157,195 |
| 2019 | 42,348,102 | 1,144,582 | -41,203,520 | 1,176,377 |
| | | | | 100,129,729 |

Table 4.8 Cost of Capital (Motor Vehicle)

| | | Motor Vehicle | | |
|---|---|---|---|---|
| **Year** | **Cost** | **Rate** | **Deviation** | **RA** |
| 2015 | 39,207,865 | 40,351,466 | (1,143,601) | 1,383,431,326 |
| 2016 | 44,486,026 | 44,886,026 | (400,000) | 12,479 |
| 2017 | 12,646,816 | 316,330 | 12,330,486 | 0.03 |
| 2018 | 13,618,583 | (95,172) | 13,713,754 | (0.01) |
| 2019 | 15,304,543 | (799,174) | (16,103,716) | (0.05) |
| | | | | 1,383,443,806 |

From table 4.7 & 4.8, the respective adjusted risk for medical claim and for motor was 100,129,729 and 1,383,443,806.

## 4.7 Summary of Data Analysis

The data that was from a normal distribution was analyzed using the various methodologies from chapter three i.e., the VAR Method, the TVAR Method, the Proportional Hazard Transform method and the Cost of capital method. The Proportional Hazard Transform was analyzed using gretl software while the rest were analyzed using Excel. From the results obtained, it indicated that VAR was the poorest indicator of the Risk Adjustment measure itself was in Trillions. The Proportional Hazard Tranform proved to be best as the model analysis proved that there was no significant impact on risks. This would imply that the hazard transform would be better suited to measuring the Risk Adjustment.

CHAPTER FIVE

# 5 SUMMARY, DISCUSSION, CONCLUSION AND RECOMMENDATION

The chapter describes the summary, discussion and recommendation based on the objectives of the study. The objectives of study were to determine the most suitable specification for risk adjustment models in the Kenyan Insurance market and to develop the model in terms of the Kenyan market.

## 5.1 Summary of findings

From the study it was found out that based on the use of value at risk (being an incoherent risk measure) the more premium contributed within the year the more the risk. This was also seen in the application of other models to determine risks. Mostly the effect of the premium on the risks was also seen as significant at $p<0.05$. The proportional hazard transform proved to be the best measure of the Risk Adjustment in the Kenyan Insurance sector as it had the ability to reflect the risk appetite in a better sophisticated manner.

## 5.2 Discussion of results

Based on use of value at risk, the risk on medical was KES 409 Trillion and risk on motor was KES 851 Trillion. This indicates that the risk preferences, key drivers of risk, the complexity of the probability or stochastic models and the ability to explain and quantify the risk adjustments in the context of financial statements. As discussed previously, risk adjustment models use large, representative populations therefore when implemented there should be an accuracy test. The researcher utilized confidence intervals to determine the accuracy and suitability of the data. (Syed Muzayan Mehmud. And Rong Yi. (2012) Uncertainty in Risk Adjustments, Society of Actuaries health selection)

Conditional Tail Expectation, medical claim premium had a conditional value at risk of about KES 3 Trillion and Motor vehicle premium had a conditional value at risk of about KES 1.8 Trillion which represents the expected loss of the worst 99 % cases. This agrees with the study by Buhlmann-Straub (1970) model combines the notion of a known risk exposure with the notion of an à prior unknown claim rate. Bühlmann and Straub model the unobserved claim rate as a random variable and derive an optimal credibility estimator to estimate the claim rate in the light of emerging claim experience.

On the Proportional Hazard Transform model, the premium for both medical and motor were found to be significant on risk at p-value 0.05. This agreed with then, estimating risk relating to reinsurance contracts will be complex without the use of a simulated approach. (Jignesh Mistry, Rob Walton (2019); Practical challenges of implementing the IFRS 17 Risk Adjustment; Institute and Faculty of Actuaries)

## 5.3 Conclusion and recommendation

The study found out that to determine the risks of policies in the Kenyan insurance market, the Proportional Hazard Transform model is the best since it explains the significance of the effects of premium on risk. Thus, to estimate risk then significance level, variance, expectation and probability distributions are required to estimate risks and these all are used by these models. Insurance companies in Kenya can estimate the risks on their products based on premium. Thus, for proper management of risks then they should manage the premium properly.

# 6 APPENDICES

## APPENDIX 1: LIST OF INSURANCE COMPANIES INCLUDED IN MODEL

AAR Insurance Kenya

African Merchant Assurance

AIG Insurance Company

Allianz Insurance Company

APA Insurance Company

Britam General Insurance

Cannon Assurance Company

CIC General Insurance Company

Corporate Insurance Company

Directline Assurance Company

Fidelity Shield Insurance

First Assurance Company

GA Insurance Company

Geminia Insurance Company

Heritage Insurance Company

ICEA Lion General Insurance

Intra-Africa Assurance

Invesco Assurance Company

Jubilee Insurance Company

Kenindia Assurance Company

Kenya Orient Insurance

Mayfair Insurance Company

Occidental Insurance Company

Pacis Insurance Company

Phoenix Of East Africa

Pioneer Insurance Company

Resolution Insurance Company

Saham Insurance Company

Sanlam Insurane Company

Takaful Insurance Of Africa

Tausi Assurance Company

The Kenyan Alliance Insurance

The Monarch Insurance

Trident Insurance Company

UAP Insurance Company

Xplico Insurance Company

## APPENDIX 2: SECTORAL PERFOMANCE AKI REPORT

| Class of Business | GWP - 2019 | % of Total Premium |
|---|---|---|
| Motor Commercial | 24,241,888 | 18.2% |
| Motor Private | 23,598,601 | 17.7% |
| Medical | 42,417,899 | 31.8% |
| Fire | 13,066,412 | 9.8% |
| Others | 30,129,914 | 22.6% |
| | 133,454,717 | 100.0% |

## APPENDIX 3: KENYAN INSURANCE SECTOR AKI REPORT

| | 2015 | 2016 | 2017 | 2018* | 2019 | 2018-2019 growth % | Average growth |
|---|---|---|---|---|---|---|---|
| Gross Earned Premium | 145.27 | 160.96 | 178.48 | 178.8 | 188.58 | 5.47% | 7.45% |
| Reinsurance ceded | 34.18 | 37.45 | 43.22 | 43.99 | 46.68 | 6.12% | 9.14% |
| Net Earned Premium | 111.09 | 123.51 | 135.27 | 134.81 | 141.9 | 5.26% | 6.93% |
| Investment & Other Income | 38.91 | 41.09 | 55.28 | 50.23 | 69.8 | 39.06% | 19.88% |
| Net Income | 150 | 164.6 | 190.54 | 185.04 | 211.76 | 14.44% | 10.29% |
| Net Incurred Claims | 81.18 | 85.41 | 110 | 111.01 | 117.3 | 5.67% | 11.12% |
| Total Commissions & Expenses | 57.96 | 64.43 | 68.53 | 69.63 | 76.36 | 9.67% | 7.94% |
| Profit/(Loss) before Taxation | 10.86 | 14.75 | 12.01 | 4.4 | 18.09 | 311.14% | 16.64% |
| Provision for Taxation | 2.92 | 5.18 | 2.66 | 1.4 | 5.4 | 285.71% | 21.23% |
| Profit/(Loss) after Taxation | 8.62 | 9.57 | 9.35 | 3 | 12.69 | 323.00% | 11.80% |

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