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Operational Risk Modeling for General Insurance Companies in Kenya

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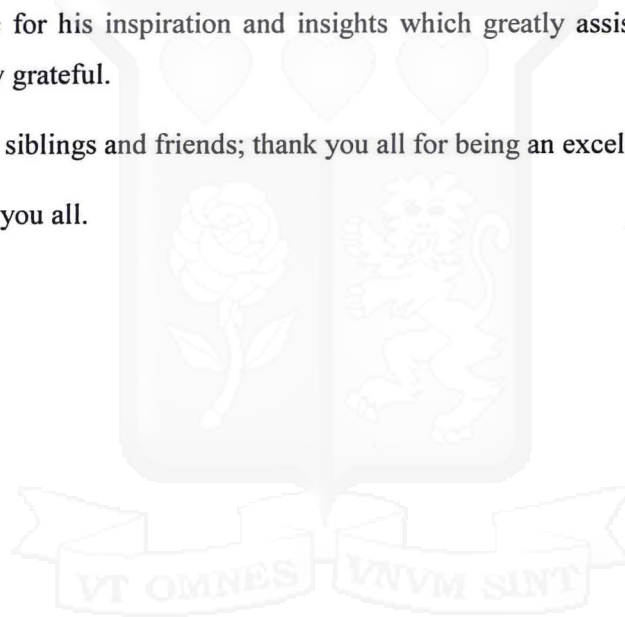


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$RBC = \sqrt{(\text{Market Risk Capital}^2 + \text{Credit Risk Capital}^2 + \text{Insurance Risk Capital}^2)} + \text{Operational Risk Capital}$	
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ABSTRACT

This study looked at the quantification of operational risk based capital for general insurance companies in Kenya. It is important to note that the regulator requires all insurance companies to compute risk based capital annually. The study pointed out the various operational risk categories and analyzed the operational risk modeling approaches that have been developed in the insurance sector globally. In Kenya, the model used by the regulator to quantify operational risk capital is that recommended by the actuarial profession in the United Kingdom (Solvency II). The main shortcomings of the model used by the regulator were cited as lack of prudence in the estimation of capital requirements and the failure to truly indicate how insurance company operations interact leading to operational losses.

The study then illustrated how a proxy-a hybrid modeling approach, could be used to quantify operational risk. The hybrid model was shown to be more prudent than the standardized approach used by the regulator. The methodology involved modeling a general insurance company and creating a hybrid simulations model for operational risk losses. Further, operational risk capital estimates were computed using the model by the regulator and the hybrid simulations model. The operational risk capital estimates were compared and tested for adequacy. The results led to the conclusion that the hybrid model yielded a more prudent operational risk capital estimate than the model used by the regulator.

Based on the overall conclusion that the standardized method may not be fully adequate in computing operational risk capital, it is hoped that this study will encourage best practice in computing operational risk capital. It is also hoped that the study increases interest in Kenya's actuarial profession in the emerging field of operational risk.

CHAPTER 1: INTRODUCTION

1.1 Background to the study

Definition of Risk and Enterprise Risk Management

Risk is defined as the exposure to actual events being different in occurrence from those expected (Institute and Faculty of Actuaries, 2016). In the financial context, cash flows are considered. The difference in actual outcomes and what was expected could be in their amount, timing or both. This is important to any financial institution as lots of effort are put into planning and forecasting various future aspects of a business such as return and budgets. Therefore, even after banks globally adopted the Basel accords, risk and its management has been practiced in the insurance sector as well. This is because risk needs to be studied, analyzed and managed.

In the promulgation and development of the Basel accords, the need for capital allocation to cover major risks in financial institutions led to the study of various types of risk. The major types of risk are credit risk, market risk, operational risk and insurance risk (Embrechts, Hansjorg, & Kaufmann, 2006).

Given the modern risk management setting, enterprise risk management has emerged. Enterprise Risk Management (ERM) is the process by which organizations in all industries assess, control, exploit, finance and monitor risks from all sources for the purpose of increasing the organization's short and long term value to its stakeholders. This process aims at maximizing the productive efficiency of a financial institution. Globally, various risk management institutes have been set up in actuarial societies to propagate the enterprise risk management function in insurance companies and actuarial functions. An example of this is the use of ERM frameworks by regulators to urge insurers to compute economic capital using risk based measures. In Kenya, the Insurance Regulatory Authority (IRA) recently adopted a risk based supervision regime. It is under this regime that insurers compute risk based capital requirements to date. For general insurers, this is done for all the general insurance products offered in the industry. They include Aviation, Engineering, Fire Domestic, Fire industrial, Liability, Marine, Motor Private, Motor Commercial, Personal Accident, Theft, Workmen's Compensation, Medical and Miscellaneous.

The standardized method used is as follows (Insurance Regulatory Authority of Kenya (IRA), 2014):

$$RBC = \sqrt{(Market Risk Capital^2 + Credit Risk Capital^2 + Insurance Risk Capital^2) + Operational Risk Capital} \quad (1)$$

Definition of Operational Risk

Operational risk is defined as the risk of loss every financial institution is expected to suffer arising from inadequate or failed internal processes, people, systems or external events (BIS, 2005). The operations of financial institutions constitute the elements that have been outlined in the definition given. It could also be defined as the link between a firm's business activities and the variation in business results (King, 2001). Operational risk is made up of only losses (Embrechts P. , 2006), and as such, the losses or loss events arising from the influence of business processes, people, systems and external events are what are studied. An example of such operational loss events is the Barings Bank operational loss event that gained international recognition in 1995 after a rogue trader brought the institution down through fraudulent trading. Another international example is the case of ING Insurance in Australia that experienced heavy losses between 2004 and 2009 because of a fraudulent accountant that embezzled 45 million AUD (Coombe.C, 2014). It is because of such great loss events globally that awareness of the need to allocate capital for the purpose of mitigating operational risk grew. Banking sector regulators began to formulate regulations necessary to see that the operational risk, just like other risks, was quantified. Soon after, the insurance sector also commenced research on operational risk with a focus on introducing a capital charge to reflect its impact in insurance operations with the same happening in Kenya.

Categorization of Operational Risk

King (2001) categorized operational losses by the sources which the loss events can be attributed to. He categorized them in the following three categories: *Accounting categorization of loss*- This comprises loss that results from incorrect or inaccurate computations made in the accounting functions of valuation, reconciliation and compliance; a further aspect that could lead to operational losses could be inaccurate timeliness in the recognizing or recording of accounting transactions in a firm, *Human factors categorization of loss*- This comprises loss that results from management oversight error, management fraud, employee activity error and employee fraud and *Value-based categorization of loss*- This comprises loss that arises from the value hierarchy of a firm; The value hierarchy comprises the core competencies and the capabilities that a firm's management considers essential to adding value to the financial institution.

Other ways of categorizing operational loss could be controllable and uncontrollable. Controllable losses are those that arise from risks that management deems it can eliminate or mitigate while business operations continue. Uncontrollable losses are those from risk events too extreme for a firm to be able to manage while performing business operations.

Ghosh (2001) categorized operational risk in terms of operational loss measures along with desired action to manage or mitigate the risks as they arise: *expected loss* whereby the desired action is to create a provision, *unexpected loss* whereby the desired action is to arrange risk based capital and *catastrophic loss* whereby the desired action is to insure against such loss.

Finally, there are seven operational risk type events outlined by Basel II: internal fraud, external fraud, employment practices & workplace safety, clients, products & business practice, damage to physical assets, business disruption & systems failures and execution, delivery & process management. They are very important because they are the units of analysis that are studied in any insurance company when it comes to studying operational risk.

Modelling Operational Risk

Since operational risk is made up of losses, it can't be traded. Therefore, insurance companies and in particular actuaries need to build models that enable them to understand loss events occurrence and their interactions in an insurance company's operations. Modelling aids the process of estimating the severity and frequency of risk events in a bid to ultimately allocate risk based capital for operational risk. It is a prevalent risk in insurance operations, and hence it can't be ignored. Regulators around the world require insurance companies to account for risks in their calculation of Solvency Capital Requirement (SCR) as required by insurance regime laws which stem from Solvency II. However, as from the definition of operational risk, the quantification may prove to be challenging because of the vastness of operational risk. Over the years many professionals such as Paul Embrechts have studied operational risk with an aim to come up with ways or models that represent the effect of operational risk in insurance companies and how to quantify it. However, it stands to remain that at present, there is no "one fits all" method to its quantification despite there being many modelling techniques. The study into operational risk can still be considered a budding field of interest though findings have been increasing.

Operational risk modelling has been done over the years using various approaches. However, being a dynamic field, more approaches have been developed and the existing ones have been improved. More detail into these approaches will be explained in Chapter 2. Solvency II suggests three methods to calculate operational risk capital charges namely the basic indicator method, the standardized method and the advanced measurement method. Both the basic indicator method and the standardized method are measurement methods based on volume. The methods are then applied to risk-based capital regimes in insurance industries in countries as well as in internal models of insurance companies for the purpose of computing solvency capital requirements.

1.2 Problem Statement

Despite the operational risk modeling approaches developed by King, (2001), Tripp, et al., (2004), Embrechts P. , (2006) and Dexter, et al., (2007), more insights need to be generated to improve on the ongoing efforts to build better models that appropriately quantify operational risk in insurance companies both in developed economies and developing economies. However, there doesn't exist a "one fits all" approach to modelling operational risk. The problem being researched on is that with only one method being used to compute operational risk capital across all insurers in Kenya, against what other method can the standardized method be compared? Comparison and testing will help to evaluate the strengths and weaknesses of the current method being used. This paper seeks to determine how adequate and appropriate the standardized method is in computing operational risk capital for general insurers in Kenya. This study suggests the need to develop of a proxy against the standardized method. It seeks to do this by proposing the use of a hybrid modelling approach which is to be discussed in the following chapter as an approach which represents the standard going forward.

1.3 Research objectives

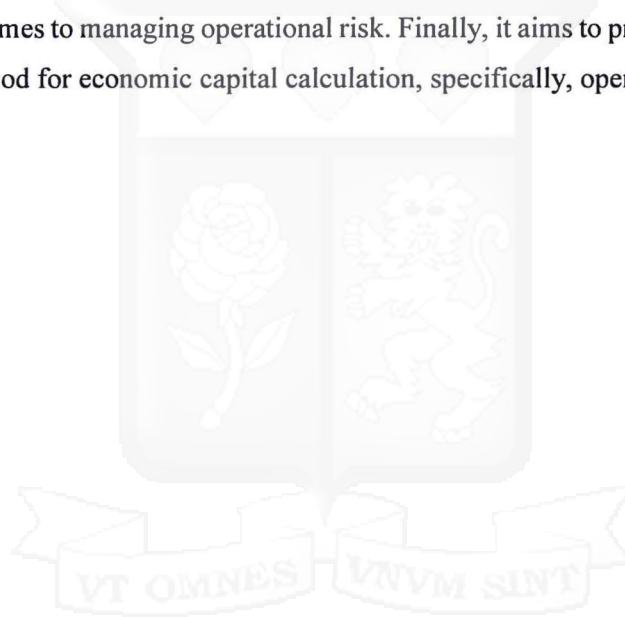
- 1.3.1 To evaluate the adequacy of use of the standardized method in computing operational risk capital for general insurers in Kenya.
- 1.3.2 To develop a proxy to the actuarial profession for modelling operational risk for general insurers in Kenya.

1.4 Research Questions

- 1.4.1 How adequate is the use of the standardized method in computing operational risk capital for general insurers in Kenya?
- 1.4.2 Does the proxy developed quantify operational risk more prudently than the standardized method used in Kenya?

1.5 Significance of Study

This study contributes to the ongoing research in the actuarial profession on operational risk modelling, with a focus on Kenya as one of the developing countries with a rapidly growing insurance sector. As such, it is helpful to the actuarial science industry in Kenya especially the Kenyan regulator in the insurance industry. It aims at increasing the knowledge base provided by Solvency II which is the current reference point for the Insurance Regulatory Authority (IRA) in Kenya in terms of operational risk capital quantification. The insights generated in this study can also inform senior management in the general insurers in this country to be able to improve current practice when it comes to managing operational risk. Finally, it aims to provide a viable alternative to the current method for economic capital calculation, specifically, operational risk capital.



CHAPTER 2: LITERATURE REVIEW

A lot of research has been done into credit risk and market risk modeling approaches with not much being done into operational risk. The following sections present research reviewed into operational risk quantification with an emphasis on the modeling approaches in an insurance and actuarial context.

2.1 Traditional Loss Distribution Approach

Literature reviewed outlined that for this modeling approach, what is required by general insurance companies is claims data. The claims data is organized and analyzed by looking at the frequency and severity of the claims. A statistical loss distribution is then fitted to the data in particular to focus on the high frequency-low severity portion of the distribution and more especially the low frequency-high severity portion of the distribution. Three major problems were identified to create consistent challenges in the quantification of operational risk in general insurance companies: sparse data, underreporting, and extreme values (Nielsen, Guillen, Bolance, & Gustafsson, 2003).

When it comes to quantification of operational risk, data could be sparse for various reasons. One of them could be that there has been no historical recording of operational losses in an insurance company. Without a historical record, there is no source of data to come up with a likelihood function in estimation of the losses. Another reason that data could be sparse is that there might be a historical record of operational losses but the amount of data is not enough to come up with reasonable estimates for operational risk charges in solvency calculations. Nielsen, et. Al (2003) proposed a methodology to curb this challenge that involves combining internal data from an insurance company with external data from other sources such as other insurance companies in the same line of business. It was found that this greatly increases the size of the sample data to be analyzed and forms a robust prior distribution. Prior knowledge refers to extra information that helps to increase the accuracy of estimating the statistical distribution of internal data. It was also found that many times insurance companies have so few observations that they need to borrow information from banks. Also, with this in mind organizations have recognized the value of obtaining loss data from outside their company, either through data sharing consortia or through publicly reported losses (Guillen, Gustafsson, & Nielsen, 2007). Publicly reported loss data could be used to supplement internal loss experience. However, this is not a case that has been seen in the Kenyan insurance industry.

In the study by Nielsen, et al., (2003) the number of observations from the internal data set used was 75 and that of the external data set was 700. It should be noted that in such a case and a similar study by the GIRO Working Party (Tripp, et al., 2004) what was used was consortium pooled data. However, it was highlighted that there was a likelihood that the results weren't as representative as they should be because the data sets incorporated from external sources may be from insurers that aren't similar to the source of the internal data set in terms of scale of business. Therefore from the above research highlighted, an assumption was made that scaling had already been done by means of a pre-scaling process. This is important to improve the accuracy of the modeling results as much as possible. A mixing model was then used to combine internal and external information and this was incorporated into four density models for operational risk. The use of semi-parametric models was proposed which is considered to be more flexible and are more suitable to the context than the normal distribution assumption. The generalized Champernowne distribution was selected as a good candidate for operational risk modeling. The distribution was initially used to model income so it was taken to adapt well to situations where the majority of observations correspond to small values, whereas a few observations correspond to extremely high values (Buch-Larsen, 2005).

This ideology holds because operational losses are always positive and as such the distribution should as much as possible be negatively skewed with the specification that the tail of the distribution should not be very thin. The challenge of this modeling approach in particular was found to be that because of the data constraints, it discourages the use of internal models to quantify operational risk.

Another aspect in modeling operational risk using the loss distribution approach is the case of underreporting. Underreporting was defined as the deliberate act of reporting less income or revenue than was actually received, usually for income tax purposes (Nielsen, Guillen, Bolance, & Gustafsson, 2003). This unfortunately could lead to underestimation of operational risk measures. Underreporting was stated to create an imbalance in how small losses and large losses from an insurance company's database are weighted in the modeling process. Therefore, to counter this, Guillen, et al., (2007), proposed the use of an underreporting function. Simply put, how the underreporting function affects the distribution is that, for small and medium-sized losses, the density function is up-weighted to include more probability mass in that domain, while larger losses are down-weighted in their domain of the distribution. Important characteristics of the

underreporting function are that it should be continuous and it should pass exactly through the predetermined reporting level values. Bearing in mind the categories of operational risk events as stated in Basel II, Guillen, et al. (2007) conducted a study into how the underreporting function adjusts the modeling approach such that it is able to make the distribution as original as possible. The operational risk categories that were used are the ones defined in Basel II for operational risk. What was presented was the estimated probability of reporting for each risk category. It was found that the event risk category number seven (which corresponds to Execution, Delivery, and Process Management) had the lowest reporting likelihood, which means that losses for this kind of operational risk are likely to be underreported. On the other hand, smaller losses that belonged to category number five (which corresponds to Clients, Products, and Systems Failure) had a much higher probability of being reported than small losses for other types of risks. It is also noteworthy that, for all event risk categories, expert opinion assesses that the probability of reporting a loss is smaller or equal than 99%, even for very large losses. In fact, this acts as a bound, and it implies that there is at least a 1% chance that a very large loss occurs and is not reported. From this study, two problems were identified. The first was that the reliance on expert opinion introduced a subjective aspect into the modeling approach that if inaccurate, could affect modeling results. Notwithstanding, expert opinion is a great aid to the modeling approach because it assists in improving estimates for each risk category depending on current economic conditions prevailing as a business continues to be operational. The second problem was that in this and similar experience in insurance companies, the fact that certain large losses could be underreported unfortunately underestimated the impact of extreme values in the loss distribution approach of modeling.

This brought about the need for discussion on extreme values and the use of extreme value theory. Here, the focus when it comes to extreme values is the tail of the distribution used in modeling. Various research initiatives elaborated the need to model the tails of the distribution and it is noteworthy to mention that the tail of the loss distribution has to be merged with the rest of the distribution in order to provide reasonable estimates that correctly reflect the level of operational risk in a company. King (2001) in his study proposed a way to merge both portions of the distribution by means of the Delta-EVTTM approach. This approach used the Delta method to estimate losses from risk factors in the business process (assignable losses), and Extreme Value Theory (EVT) for large losses due to control breakdowns and external events (unassignable

losses). A threshold was then used to separate losses to be analyzed using the Delta method from those to be analyzed using EVT. The Delta method was used to set the maximum loss threshold that determined the classification of 'large losses' to be modelled using EVT. The Delta method uses factors that lead to loss and their sensitivities to generate loss distributions in the business unit. EVT was used to deal with the tails of the distributions and to set the minimum loss threshold that defined a minimum large loss. EVT included a parametric model that, given a series of large losses, could be used to predict the occurrence of losses that had not yet happened i.e. outside the data range. The approach worked well to cater for both assignable and unassignable losses. It was found that a challenge of using this approach was that given that a parametric model was included, it was difficult to select the best appropriate distribution to fit to the insurance company data. Such a situation would greatly inhibit operational risk quantification in Kenya.

Overall, it was seen from literature that in addition to the need to fit a statistical loss distribution to the data, the looming question was what should be the best model that should be fitted to the data. Also, both the use of either a parametric or semi-parametric approach have their advantages or disadvantages in terms of how much data needs to be used in order to get reliable operational risk estimates.

2.2 Causal Models for Operational Risk

Literature reviewed suggested that under this approach, models used sought to explain operational risk in terms of looking at it from a cause-and-effect angle. Here, the effect would be the estimates of operational risk for insurance companies. The cause would be changes in the various risk factors that constitute the risk categories identified in an insurance company.

Tripp, et al., (2004), conducted a study by applying the use of causal models to a situation of an insurance company example. They built a model that was meant to clearly show the causal chain that brought out a particular risk outcome and its impact on the company. For this study, only one of the risk losses was analyzed. In the model development a risk map was used. It showed the connection between internal underlying causes, external underlying causes, failed processes, risk decisions made and the financial outcomes. Those elements of the risk map greatly borrow from the operational risk categories stated by Basel II. The risk map was then translated into a causal model for that particular risk loss. From the results it was noted that failed processes and internal drivers provided a weak score. Faulty risk decisions were then created. Further, it was investigated

how different levels of outcome evaluation affected the model's output. Outcomes with high policyholder harm were determined to have little or no negative impact on policyholders. Outcomes labelled as disasters were determined to have a negative impact on policyholders. It was noted after this that with such a model, improving the outcome evaluation from weak to strong reduced the likelihood of disaster outputs. The nodes in the model that got disaster probabilities were considered as the areas that management needed to direct urgent attention to so as to reduce the company's operational risk. An advantage of this model was that it clearly distinguished between risk events and risk outcomes. For an insurance context this is good as such knowledge is required to understand the operational risk profile of a general insurer. It also helped to make clear management decisions that would result in adverse outcome. Conversely, even though the model was termed as 'simple', it had challenges too. First, such a model would require a heavy investment of resources because of the complexity of the underlying chains in the process. It also lacked a feature to update the model when more data became available so as to be able to revise the output. This was a great downside because operational risk is dynamic and such a quality should be captured in the modeling process.

To improve on the earlier study as given above, the use of Bayesian networks was proposed in the study done by Cowell, Verall, & Yoon (2007). These Bayesian networks are designed to model various risk factors and their combination into an overall loss distribution. They feature the use of subjective opinion which is combined with observed data to capture the workings of a financial institution. Underlying Bayesian Networks is the Bayesian statistical framework that enables the combination of subjective input with empirical observations. This is very adaptable to situations with a high level of uncertainty, and where data are costly or sparse, two intrinsic features of Operational risk (Cowell, Verall, & Yoon, 2007). From this study, one of the advantages noted was that since operational risk occurs in a dynamic setting, then Bayesian networks are able to be get updated with more information as it comes in. On the flip side, it was noted that because the approach heavily relies on data, the output's reliability could only increase with increase in available data. The availability of high amounts of data could be a challenge to many general insurers in Kenya. What drove the study into this approach to modeling operational risk is that operational risk needs to be dealt with in terms of causes rather than effects (i.e., the loss event), as a financial loss may have various underlying causes, which may or may not be operational (Cowell, Verall, & Yoon, 2007). In the study, an insurance fraud example was considered.

Insurance fraud was a good choice for the study because it falls in one of the categories of operational risk (External Fraud) as stipulated by Basel II. The example was set up to illustrate how a Bayesian Network can be constructed using a combination of past data and expert input. What was considered in particular was the application of Bayesian Networks to model a specific operational risk event common to insurance companies: fraudulent claims. It was highlighted that efforts to monitor how and when fraudulent claims occur are costly and would not always succeed in eliminating fraudulent claims payouts. The level of control in claims management in turn was stated to depend on the experience of the claims assessor; more experienced claims assessor are more able to detect fraudulent claims, the use of the services of a loss adjuster; loss adjusters specialize in assessing the amount of loss suffered in a fire & this helps to mitigate artificially inflated claims and random checks - the company may carry out random checks on claim files for more detailed assessment before approval of payment.

The following figures illustrate the insurance fraud example that was set up.

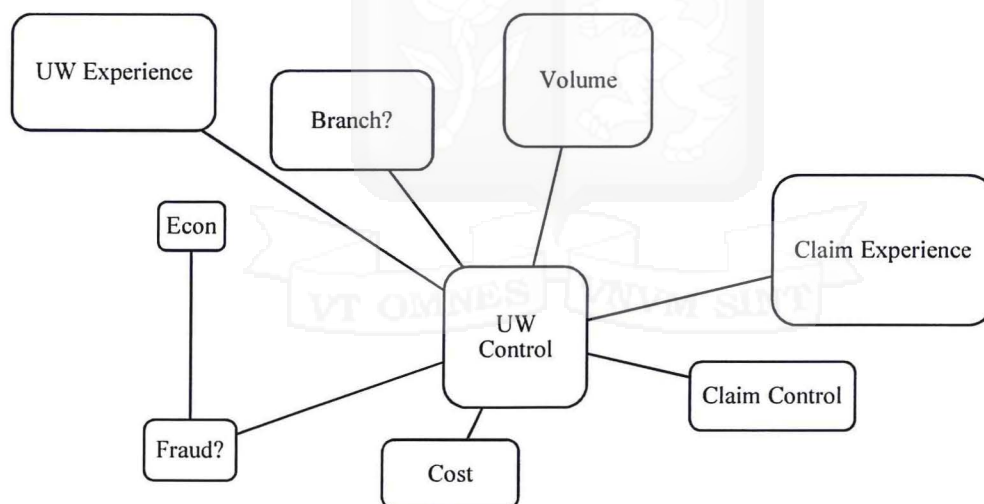


Figure 1 - Direct Acyclic Graph of Insurance Fraud Example (Cowell, Verall, & Yoon, 2007)

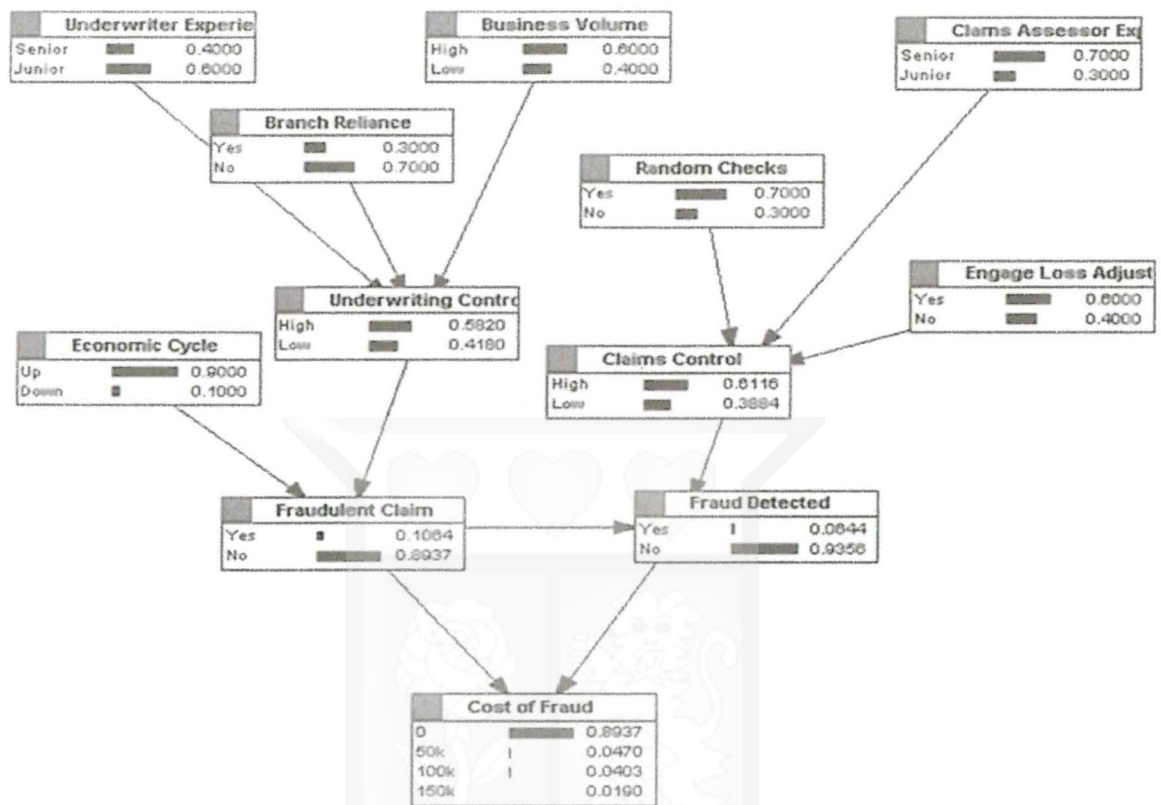


Figure 2 - Prior Marginal Distributions Used in Insurance Fraud example (Cowell, Verall, & Yoon, 2007)

The random variables that were analyzed in this Bayesian Network were: underwriter experience, branch reliance, business volume, claims assessor experience, random checks, engaged loss adjusters, underwriting control, claims control, economic cycle, and fraudulent claim, fraud detected and finally cost of fraud.

It was noted that an actuarial function in an insurance company can set up a Bayesian Network with a two-pronged strategy: to identify what causes the events that lead to operational risk losses and to help the management to decide how much risk capital should be allocated to cover the loss from such events in all but the most extreme of scenarios (Cowell, Verall, & Yoon, 2007). At the prior stages of setting up the Bayesian network, specification was made on the Direct Acyclic Graph on the need to populate prior probabilities at each node. (The Direct Acyclic Graph is a diagram of the model that shows the interactions between the various nodes of the Bayesian Network). These would be the unconditional prior distribution for nodes without parents and

conditional prior distributions for child nodes. Considering two nodes, should there exist a direct dependence between them, whenever new information is introduced into say, node A, a change in node A could then cause a change in node B. In this case, node A becomes the parent node and node B becomes the child node. When a non-direct dependence exists between nodes for instance in the form of correlation, the nodes A and B are termed as neighbors. Should no form of dependence exist between nodes A and B, then they are considered to be independent of each other. The graph is termed as acyclic because on transition from one node to the other, it is not possible to return to the prior node as would be the case in a cyclical loop (Cowell, Verall, & Yoon, 2007). For each prior, probabilities are needed for each configuration of the combination of states of variables involved. Those are to be determined by subjective opinion of the expert involved in the process. Experts were interviewed in a series of questionnaires to arrive at quantified conclusions of the probabilities. Sufficient confidence in the accuracy of the expert's advice is a prerequisite to use this method. Maximum likelihood estimation was then used as the estimation method with complete data. The availability of complete data is not always the case in insurance companies. For unconditional priors, this would simply be the proportion of occurrence between the various states of the variable. For conditional priors like in the study above, this method would entail taking a ratio of frequency of the event to the frequency of the parent configuration and also deriving the maximum likelihood estimation with incomplete data.

The model was assessed by means of logarithmic scores which measured the level of "surprise" at each data point. It was given by:

$$S_m = - \log P_m (Y_m) \quad (2)$$

Where $P_m ()$ is the predictive distribution for the event, Y_m , after $m-1$ occurrences of events. If learning is allowed then $P_m ()$ incorporates all updates resulting from the $m-1$ events. The S_m is the negative log of the probability of the event in the actual outcome Y_m . The less likely an event is predicted to happen, the more "surprising" it is if it did happen and as such the logarithmic score would be high.

The main advantages of using Bayesian Networks for modeling operational risk is the allowance to incorporate expert opinion through: Choice of the variables of interest; Definition of the structure of the model via the causal dependencies, and Specification of the prior distributions and the conditional probabilities at each node (Cowell, Verall, & Yoon, 2007). Bayesian statistical

methodology ensures that the model can quickly adapt to new input and incorporate it with prior expert opinion in a mathematically amenable manner. This could be considered an improvement from earlier studies. Monitors are also available to enable the strength of such a process to be observed in real time, thus facilitating informed model criticism and choice. This approach to modelling operational risk can be incorporated in insurers' internal models as insurers seek to set supervisory capital as required by supervisory regimes. This could also be considered a better approach to modeling as compared to the loss distribution approach which greatly discouraged the use of internal models. The graphical presentation of Bayesian Networks helps stakeholders understand the causal structure and risk profile of an insurance company which can help to improve the management's understanding of how operational risk works and how it can best be managed.

One of the challenges of modeling operational risk using Bayesian Networks is that the model can get complex if there are many nodes that need to be specified. In such cases, there can be many conditional probabilities to specify, which will require a significant volume of data if the maximum likelihood method of estimating probabilities is used. Also, there arises an issue as to what the suitable model structure should be in coming up with the causal dependencies. Such a case creates inconsistencies and this could make the comparison of models rather difficult. This further illustrates the absence of a "one fits all" approach to modeling operational risk.

2.3 Modeling Operational Risk Using Coherent Risk Measures

Literature reviewed suggested that this approach entails using coherent risk measures to obtain single-loss estimates for operational risk. The most common way of estimating the amount of equity reserve for operational risk is by using the risk measure Value at Risk (VaR) (Biagini & Ulmer, 2009). Value at Risk is popular because of its straightforward nature and its ability to be computed easily given a stipulated confidence interval. However, an essential disadvantage of it as a measure of operational risk and risk in general is that it is not a coherent measure. This means that it does not produce consistent results.

A multivariate operational expected shortfall model was developed which incorporated the fact that since operational risks are always losses, there had to be a concentration on Lévy processes admitting only positive jumps in every component, thereafter called spectrally positive Lévy processes (Bocker & Kluppelberg, 2007). An advantage of the study was that since the model used was a multivariate model, it captured the nature of operational risk as being influenced by many

risk factors. The conclusion of the study elaborated that the use of Value at Risk approach to compute a single operational loss estimate was too optimistic. Therefore, it was agreeable that such as case would only underestimate the potentially severe tail loss events which form the greater part of operational risk capital. This rendered it less practical for modeling purposes even in the Kenyan context.

A study done by Biagini and Ulmer in 2009 proposed the use of Expected Shortfall which is usually the next best alternative to Value at Risk. It is also known as Average Value at Risk, Conditional Value at Risk and Tail Value at Risk. For the case of general insurance it is a suitable approach because by including focus on the tails of loss distributions, it conservatively enables a risk analyst to, at the same confidence level of a VaR, regard the sizes of extremely high losses that occur with a low probability. The assumptions in this study were that the actual loss profile exhibited several extremely high losses with a very low probability and that operational risk followed the traditional loss distribution approach. However, one disadvantage was that all this was only considered for a univariate case hence ignoring the nature of operational risk in a general insurer. It was inconclusive as to whether this could be done for more variables. In addition, if the multi-variate case were possible, would the single loss estimate produced by the operational expected shortfall adequately cater for the correlations between the variables being modeled? There is also the possibility that for the multi-variate case, the modeling process would be very time intensive. Finally, It can be inferred that using coherent risk measures still rely on data and so if not enough data is available then the single loss estimate of operational risk capital computed may not be as accurate as would be required.

2.4 Hybrid Modeling

Literature reviewed suggested that this modeling approach is upcoming and it constitutes the use of a combination of both scenario analysis and loss distribution data. The Insurance Regulation Committee in Canada defined a scenario as a consistent future state of the world over time resulting from reasonable or credible and perhaps adverse events or sets of events (IAA, 2013). Scenario analysis is the process of estimating the expected value of a certain figure or entity of interest given a period of time, assuming specific changes in the entity's factors. It aims to test the entity's response to unfavorable events such as in this case, how the level of capital requirement for operational risk shifts given changes in various risk factors. For this approach, what is modeled is the various risk categories of an insurance business as outlined in the ORIC International Taxonomy whereby the risk categories are divided into Level 1 and Level 2. The operational risk event types as stated in Basel II could also be modeled given a hybrid model.

It is worth noting that from the report CIA (2014), of the study done by Corrigan & Luraschi whereby operational risk capital was computed under a quantitative risk assessment, the following elements were found to be vital in a hybrid operational risk framework: governance, preparation, assessment, validation, reporting and evaluation (Corrogon & Luraschi, 2013).

The Institute of Risk Management (2015), found out from a study it conducted that there is a variety of approaches that insurance firms have developed over the years in the absence of any detailed regulatory guidance to model operational risk. That notwithstanding, the study showed that hybrid models have become the most popular approach in countries in the Operational Risk Insurance Consortium (ORIC). The following diagram illustrates those results.

Types of models



Figure 3 - Types of models and their current popularity in OP Risk modeling (The Institute of Risk Management, 2015)

In the diagram above, the various existing approaches of modeling operational risk are shown.

In the diagram above, the various existing approaches of modeling operational risk are shown. Perhaps a similar study can be done in Kenya and East Africa to see if similar results can be achieved.

One of the advantages it has is that it can be incorporated into insurance companies' internal models and it can be adapted to all the insurance business types namely general, life, reinsurance and composite insurance companies. An approach that is purely data-driven is not feasible for many insurers because of the lack of enough data to produce reliable results. Therefore, there is need to tend towards scenario-based approaches. Hybrid modeling also involves the use of expert judgement and use of validation techniques to ensure that results are appropriate. Because of these advantages that make hybrid modeling superior over the other approaches, this research project aims to apply the concepts of hybrid modeling to come up with a hybrid model for the Kenyan general insurance industry context to serve as a proxy to the standardized method for computing operational risk capital.

2.5 Research Gap

Regulators require insurers to measure operational risk capital as part of indicators for solvency. Taking the case of Kenya, the Insurance Regulatory Authority requires the insurance companies locally to submit data-filled templates of financials that are geared towards calculating the solvency capital requirement as adapted from Solvency II in the United Kingdom. In Kenya, the standardized method of computing the operational risk charge is used. The operational risk charge is equal to greater of 3% of gross earned premiums during the previous 12 months and 3% of gross technical provisions, with the result being subjected to a maximum of 30% of the basic SCR. It is assumed that there is no diversification credit between operational risk and other components of risk (IFOA, 2016). In Kenya, some adjustments may have been made to those percentage values in scale of the size of the insurance business in Kenya but the approach is the same. The gap in this area of risk management is that there is need for another modeling approach to be developed in Kenya to test whether the operational risk capital being estimated for each general insurance company in Kenya provides accurate estimates. Hence one of the research objectives of this research project is to propose a proxy to Kenya's general insurance industry for the purpose of modeling to compare and test the suitability of the method currently being used.

Another research gap that is vivid from the literature reviewed is that most, if not all of the research that has been conducted in the field of operational risk modeling has only been done in developed countries like United States and United Kingdom. There is need for such work and even advancements to ongoing work to be done in developing countries like Kenya. Such research can stimulate massive growth in the insurance sector of not only Kenya but surrounding developing countries in the region which have growing insurance sectors.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Design

The study was done using a quantitative analysis approach since the objective of the study was to develop a proxy model to compute operational risk capital. The research was cross-sectional since it was conducted at one point in time in an assumed financial year when a general insurance company is required to compute risk based capital.

3.2 Population and Sampling

According to IRA (2017), there are forty-two insurance companies in Kenya. To break this down, there are six life insurance companies, seventeen general insurance companies and nineteen composite insurance companies. For the purpose of this study, the population will be the composite and general insurance companies. The reason that the composite insurers have been included in the population is that they also have general insurance functions. The study focuses on the general insurance industry in Kenya because the time period of analysis of general insurance is a year in which operations take place. Claims are evaluated on an annual basis and since claims occur at a high frequency, data is readily available. This makes the analysis of data easier. The sample chosen for the study consists of the following five insurance companies: Jubilee Insurance Company, UAP Insurance Company, Britam General Insurance Company, APA Insurance Company and CIC General Insurance Company. The five companies were selected because they have the largest market share in the general insurance industry in Kenya, hence being a good representative of the population.

3.3 Data Collection

For the five companies in the sample, quantitative data such as claims data, premium income and GDP contribution will be obtained from quarterly industry statistics by the IRA. The statistics provided by the regulator can be assumed to be accurate for the purposes of this study. Further data for the insurance companies may be gotten from the Association of Kenya Insurers studies whose data may also be assumed to be accurate.

For the model that will be designed for the proxy, loss data will be simulated for purposes of comparison with the standardized method of computing operational risk capital.

3.4 Modeling

3.4.1 Modeling MGI General Insurance Company

For the purpose of this study, the hypothetical company created during the simulation process was labeled as “MGI General Insurance Company”. Any resemblance to any real financial institution in the industry is purely coincidental. For the simulations made, it was ensured that the data was based in reality (sourced from both public and private sources), practical and easy to apply in a general insurance case. It was also deemed reasonable that the year of financial simulations would be as at 2016 for the purposes of computing operational risk capital requirements. Subsequent computations and analysis for the current year 2017 would not have been possible until the beginning of the year 2018.

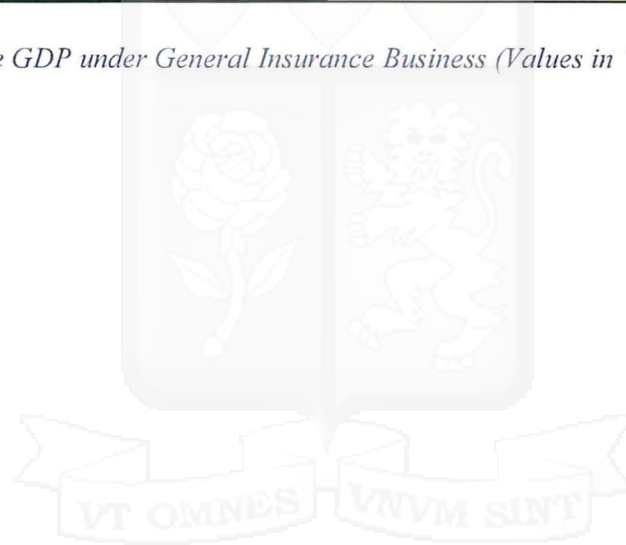
The assumptions used in the modeling process for the hypothetical insurance company were as follows:

Products Offered

For the purpose of providing a generalized case that represents the whole industry, financial statements were created for Motor Private Insurance business that included both liability and property damage for MGI. Further, consolidated financial statements were developed for MGI which involved scaling up the financials for motor private business. From analysis of the IRA 2016 statistics, motor private business was determined to constitute about 16.8% of total general insurance business. An assumption made here was that the same case applies for MGI. The financials simulated were then scaled up by a factor of 5.95 to compute 100%, which are the consolidated general insurance company financials. Based on these assumptions, a further assumption was that for MGI, the business experience for other products offered is similar to that for Motor Private. Another rationale for choosing to initially model motor private insurance is that since it is a legal requirement for Kenyan motorists to purchase insurance cover for their vehicles, it is expected that all general insurance companies in Kenya offer it as a product. The table below illustrates this.

Classwise GDP under General Insurance	Proportion of Total Business
Aviation	1,476,801.00 1.2%
Engineering	3,473,125.00 2.9%
Fire Domestic	1,482,865.00 1.2%
Fire industrial	10,062,935.00 8.3%
Liability	2,520,106.00 2.1%
Marine	2,604,270.00 2.1%
Motor Private	20,460,256.00 16.8%
Motor Commercial	24,025,770.00 19.7%
Personal Accident	3,997,282.00 3.3%
Theft	3,774,820.00 3.1%
Workmen's Compensation	5,601,571.00 4.6%
Medical	38,520,439.00 31.6%
Miscellaneous	3,710,221.00 3.0%
Total	121,710,461.00 100.0%

Table 1-Class wise GDP under General Insurance Business (Values in '000s KES)



Financial Statements

Assumption	Value	Rationale
Premium Rate	4.25%	This tends to be the average competitive rate for general insurers in Kenya.
Average Sum Insured	KES 1,000,000	This tends to be the average value of most vehicles in Kenya.
Loss Ratio	70%	
Policies Renewal rate	80%	To ensure profitability.
Delay in claim payments	3 months	Is the current practice in Kenya.
Commission rate	10%	Prudent minimum
Management Fees charge	10%	Prudent minimum
Reinsurance rate & recoveries (proportional reinsurance)	40%	Prudent minimum
Reinsurance commission	10%	Prudent minimum
Investment return	10%	Most prudent rate of return (bare minimum) a financial institution would yield on investments.
New Policies are assumed to come from a normal distribution.	Mean = 400 Standard deviation = 10% of mean	Reasonable in Kenyan industry.
Shareholder's capital	KES 600,000,000	Is the minimum amount of capital that the regulator requires a general insurer to hold.

Table 2-Financial Statements Parameters Assumptions

Additional Assumptions

MGI is a local general insurer with no international affiliations or partnerships.

MGI began operations in the year 2014 when the new solvency capital regime was instituted by the regulator in Kenya. As such, financial simulations were generated for 3 years (2014 = Year 1, 2015 = Year 2 and 2016 = Year 3).

There have been no management or staff changes, especially in terms of numbers in MGI since it began operations.

Claims handling is done in-house.

The Motor Private product modeled is of the comprehensive nature.

No taxation treatment has been assumed for MGI General Insurance Company.

All profits are ploughed back into the business with no acquisition of fixed assets made to date.

3.4.2 IRA Model

Once results were gotten from the MGI General Insurance Company model, the financial data simulations for the modeled general insurance company were used to calculate the operational risk capital as per the method prescribed by the IRA. The data for the other 5 companies in the sample was also run in the IRA model to compute their respective operational risk capital estimates. The values arrived at were compared with that of the simulated company for the purpose of testing reasonableness of the results gotten from the simulated company model. The IRA model involved first computing credit risk capital. Then followed calculations for market risk and insurance risk capital. Finally, a sum of squares was done and the values of operational risk gotten from the square root of the sum of squares in the model.

3.4.3 Hybrid Simulations Model

The modeling approach was similar to that in the study done by Dexter, et al., (2007). The steps of the modeling process to generate combined scenarios was as follows. First, using the operational risk categories as stated in Basel II, an appropriate base risk event was selected. Second, all the potential causes of that risk event were considered. The rationale for this is that it is required that the number of overlaps with other operational risk categories is low. It is also be required that the

optimum number of scenarios is achieved. About ten thousand simulations are to be made using the model. This was done to generate daily scenarios for each month of operations for the modeled general insurance company. Further, possible outcomes of the scenarios were identified. Third, expert opinion was involved in the modeling process to be able to evaluate what plausible scenarios are, given the experts' vast knowledge of general insurance systems & controls and potential causes and effects of the scenario. The modeling process was clearly defined and will be repeatable. The results were documented. Ultimately, the operational risk capital estimate that required assessment was identified. The following method was used:

Let L_i be the scenario loss for the i^{th} OR approximately equal to the required percentile from the tail of :

$$\sum_{j=1}^{N_i} X_{ij} \quad (3)$$

It is then necessary to aggregate across the K scenario losses to estimate the percentile loss from the tail of the aggregate loss distribution. The operational risk capital estimate is calculated as follows:

$$ORCA = \text{Agg} (\{L_{ij}\}, \{p_{ij}\}) \quad (4)$$

Where $i, j = 1, 2, \dots, K$ and p_{ij} is the correlation between OR i and j . This aggregation was performed using an aggregation formula such as root sum of squares allowing for correlations.

The above method required a K by K matrix of pair-wise correlation estimates. The correlation estimates had to be for the relationship between total losses, rather than the frequency or severity of loss events for each risk.

The hybrid model created took the design of a risk register with an allowance for each month of the year since it was assumed that business is carried out all year round. Further, the following design assumptions were used for the simulation of operational risk capital. A Monte Carlo simulation technique was used.

Assumptions.

The systems in MGI are fully automated.

The systems are reviewed daily to make sure controls are implemented with trained and motivated staff that are motivated to work in an appropriate cultural environment.

Main risks assumed to be focused on in this case were internal fraud, external fraud, systems development, IT interruptions and implementation of strategic decisions. These were deemed to be the more dominant risk categories faced by many general insurance companies in Kenya. Any fraud incidents were assumed to be reported by an employee of MGI.

Operational losses are recorded from the various aspects of the business and totaled daily before aggregation is done at the end of the month.

Simulation Parameters.

Lower Limit	0
Upper Limit	2,000,000.00
Confidence Interval	95%
Alpha	5%
Operation Days	Number of days in that month

Table 3- Simulation Parameters

Model Simulation

Using Monte Carlo simulation, random operational loss amounts were generated for each operation day of each operation month. Since operational losses are assumed to be positive, then the rational lower limit chosen was zero. The upper limit was chosen as KES 2,000,000 because it was tested in the model and seen that this estimated value yields a low correlation of loss amounts monthly.

The operational risk capital estimate (ORCA) was then calculated using an actuarial aggregation technique (Dexter, et al., 2007) as noted in equation 4, which involved finding the root of the sum of squares. Here, the squares were the totals of the simulated operational risk amounts in each month. Taking each month to be a point of reference for the loss amounts, the aggregation was calculated as follows:

$$ORCA = \sqrt{((January\ Total)^2 + (February\ Total)^2 + \dots + (December\ Total)^2)} \quad (5)$$

CHAPTER 4: RESULTS AND DISCUSSION

The industry averages used in the modeling process of MGI were based on the IRA 2016 Annual Report. Further, solvency capital requirements data was available for all general insurance companies. This and the risk based capital template used by the IRA for its model was made available by the Association of Kenya Insurers via Kenbright Actuarial and Financial Services.

The year chosen for the study was 2016. This is because, since the computation of solvency risk capital is done annually, the last reference point was 2016. 2017 data will most likely be available in Quarter 1 next year. Therefore, the study assumed a retrospective approach. In addition, it was assumed that MGI, just like the present insurance companies in Kenya, is a going concern.

As expected, which is rather a weakness of this study for now, the general insurers in the sample as per the research design were reluctant to provide operational loss data. Further, not many insurance companies kept operational loss databases. Therefore, this necessitated the need to model MGI and further, simulate operational loss data for the purpose of analysis to be able to draw insights and conclusions.

4.1 Preliminary Results – The IRA Model

It is worth noting that the Solvency II model used to compute solvency capital requirements in this case, operational risk was used to calculate ORCA for both the companies in the sample and MGI.

Risk Charge	Credit Risk Capital	Market Risk Capital	Insurance Risk Capital	Operational Risk Capital
Jubilee	2,564,832,016	1,277,411,579	4,963,290,998	3,295,634,074
UAP	3,865,409,048	1,565,870,213	3,743,754,244	2,346,521,653
Britam	618,991,262	156,011,498	2,673,371,040	2,374,105,780
APA	1,872,395,218	948,614,281	773,837,374	642,485,556
CIC	1,401,236,409	657,520,736	4,771,089,108	2,897,097,682
MGI	1,831,563,973	180,000,000	531,319,432	574,664,618

Table 4-Risk Based Capital Charges as at 2016 (Values in KES)

To give a more visual presentation of the results, the following bar graph illustrates the risk based capital components from Table 4 above.

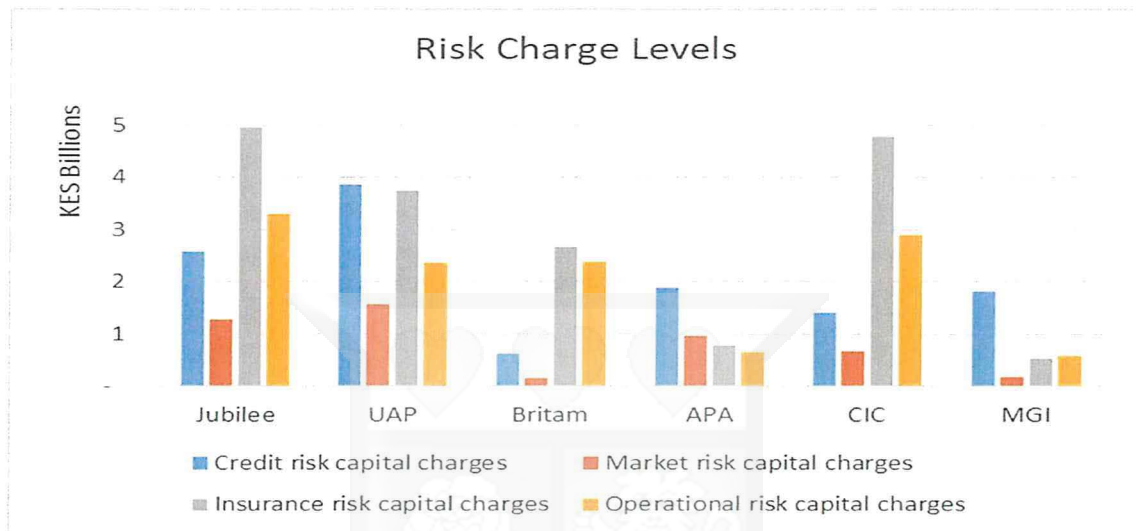


Figure 4-Risk Charge breakdown (Billions KES)

From this it was inferred that the larger industry players such as Jubilee, UAP and CIC had to set aside very large amounts of capital for the various risk types. Further, it was noted that MGI's risk charges were within the range of the charges of APA and hence could be assumed to have an almost similar size and level of risk. For the companies above, credit risk and insurance risk charges had the largest share of total risk based capital.

Further, the credit risk charge for MGI was seen to be high in the overall RBC charge as compared to the other companies in the sample and also in the industry. This is because of the high amount of cash and bank balances yielded in the simulation, noting that it was assumed that there were no borrowing or credit facilities use by MGI.

In summary, MGI was considered to be similar to the companies in the sample based on the results gotten.

4.2 Research Results - The Hybrid Simulations Model

As per actuarial modeling simulation requirements, the model was run 10,000 times. It was also ensured that the model was dynamic to ensure that a company that uses it as a template can adjust the assumptions and parameters to be able to yield company-specific results.

Descriptive statistics were generated for the operational losses simulated per month for MGI.

Further, a correlation matrix was generated for the operational losses data simulated by the model. It is presented below:

	January	February	March	April	May	June	July	August	September	October	November	December
January	1.00	0.03	0.04	0.34	0.00	-0.04	0.05	-0.42	0.14	-0.17	0.07	-0.20
February	0.03	1.00	-0.13	0.08	-0.31	-0.14	-0.08	0.14	0.31	-0.26	0.02	-0.24
March	0.04	-0.13	1.00	0.03	-0.17	-0.06	-0.27	-0.07	-0.02	0.02	0.21	0.00
April	0.34	0.08	0.03	1.00	-0.06	0.20	0.03	0.10	0.38	0.03	0.28	0.02
May	0.00	-0.31	-0.17	-0.06	1.00	0.21	0.02	-0.05	0.13	0.02	0.28	0.32
June	-0.04	-0.14	-0.06	0.20	0.21	1.00	0.17	0.24	0.18	-0.14	0.00	0.00
July	0.05	-0.08	-0.27	0.03	0.02	0.17	1.00	-0.10	0.29	-0.26	0.17	-0.03
August	-0.42	0.14	-0.07	0.10	-0.05	0.24	-0.10	1.00	0.04	-0.21	-0.07	-0.05
September	0.14	0.31	-0.02	0.38	0.13	0.18	0.29	0.04	1.00	-0.26	0.08	0.02
October	-0.17	-0.26	0.02	0.03	0.02	-0.14	-0.26	-0.21	-0.26	1.00	-0.07	0.36
November	0.07	0.02	0.21	0.28	0.28	0.00	0.17	-0.07	0.08	-0.07	1.00	-0.12
December	-0.20	-0.24	0.00	0.02	0.32	0.00	-0.03	-0.05	0.02	0.36	-0.12	1.00

Figure 5-Correlation matrix of the simulated operational losses for MGI

The cells in the correlation matrix highlighted in red are negative correlations while those in gold are positive correlations. It was noted that the highest positive correlation was shown to be about 0.36 and the lowest positive correlation was shown to be about -0.31. Both are shown to be low values. The values have been rounded off to two decimal places.

From the correlation matrix in figure 5, it is worth noting that the values of the maximum and minimum correlation highlighted were low. This is to be expected and is close to the ideal situation for an operational risk data model. A low correlation indicates that there are little to no overlaps among the risk categories in the modeling process. This should be the case for such a model as the hybrid simulations model.

It should be noted however that since the model was dynamic, in this case, there could be instances whereby the data led to a situation whereby the operational loss amounts were strongly correlated and hence indicated events in the business process or system that could have led to large operational losses. In such a case, the correlation between operational risk losses of such high amounts and catastrophic risk losses should be investigated to again try and minimize the correlation hence reducing overlap.

The total estimated operational loss amounts for MGI are presented as follows:

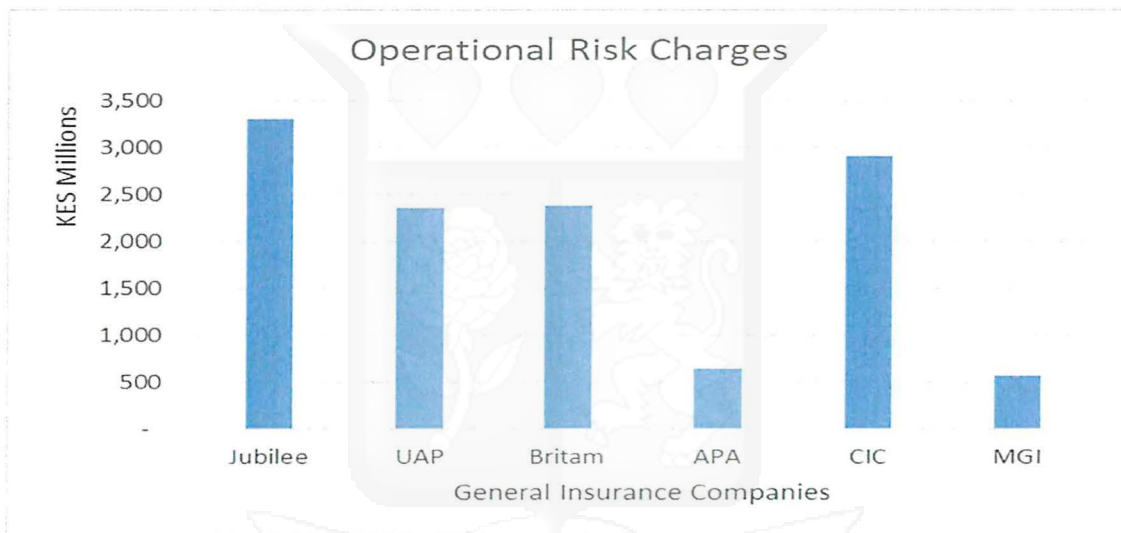


Figure 6-Total Operational Loss Estimates per month

It should be noted that the loss estimates here were also scaled up from estimates simulated for Motor Private Business in MGI. The scaling up was to compute overall estimates for MGI in its entirety.

After the simulation results and ORCA from the IRA model were computed, the following infographic highlights the output from the models when compared.

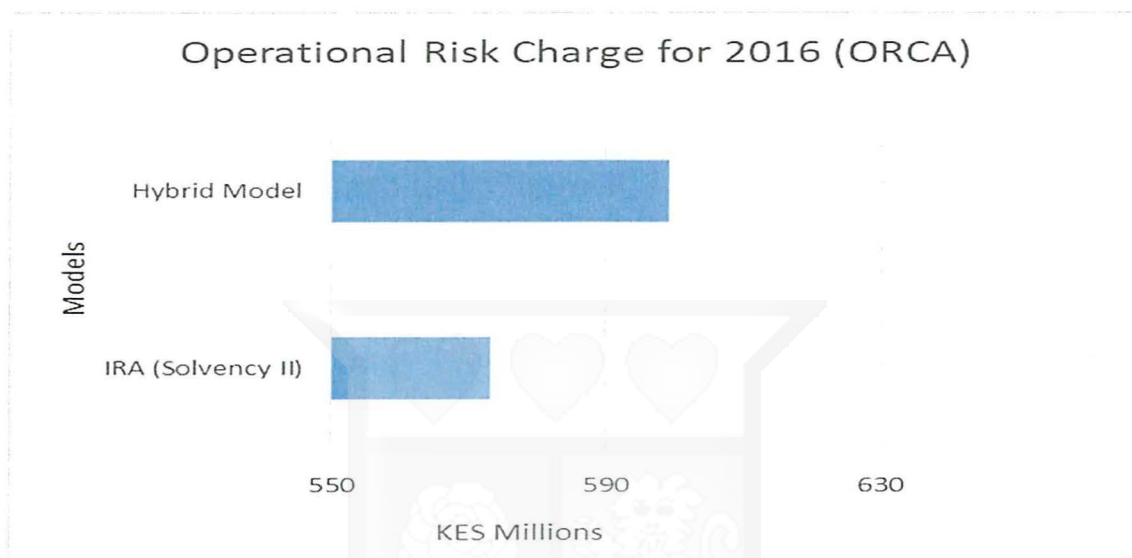


Figure 7-Operational Risk Charge for 2016 (ORCA)

It was noted that from the simulation, the hybrid model yielded a higher operational risk charge than the charge computed using the IRA model.

For the outputs, those being the operational risk capital estimates from both the IRA model and the Hybrid model, a simple hypothesis test was conducted. One of the objectives of this research project was to prove whether a hybrid simulations model and the IRA model are both equivalent measures of operational risk capital.

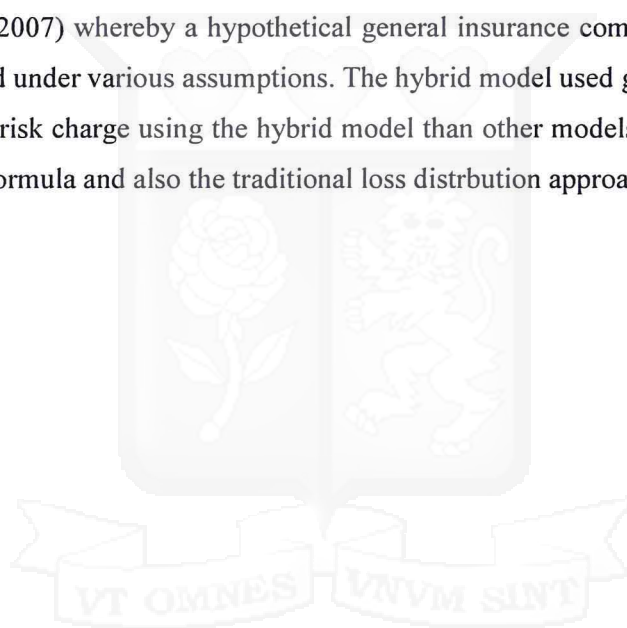
As such, the hypothesis test was as follows:

H_0 : $OPSCR_{IRA}$ is equal to $OPSCR_{SIMULATIONS}$

H_1 : $OPSCR_{IRA}$ is not equal to $OPSCR_{SIMULATIONS}$

Once the outputs from both models were compared after many simulations, it was concluded that the model yielded a higher value of operational risk capital than the IRA model and as such the null hypothesis was rejected at the 5% level of significance.

Figure 7 above shows the results of the output which presents the results of the simulations after they had been run. Given that the simulations were done at a 95% confidence interval, the results showed that using a hybrid model with prudent (bare minimum) assumptions computed a relatively higher level of operational risk capital once the operational losses per month had been aggregated at the end of the year using the aggregation formula as shown in equation 4. The difference in operational risk capital calculated using both models wasn't overly dramatic. However, if the results of this study are anything to go by, then the hybrid simulations model provides a more prudent approach to computing operational risk capital. Similar results arrived at in the study done by Dexter, et al., (2007) whereby a hypothetical general insurance company was created and its operations modeled under various assumptions. The hybrid model used got results that reflected a higher operational risk charge using the hybrid model than other models tested in the study such as a standardized formula and also the traditional loss distribution approach.



CHAPTER 5: POLICY IMPLICATIONS

The findings above indicate that while general insurance companies in Kenya have for the past 2 to 3 years adopted the standardized approach to computing operational risk capital, there are more prudent approaches such as hybrid modeling to be able to compute more accurate operational risk capital estimates as required by the regulator. The framework used in hybrid modeling shows in detail how risk events occur in the operations of a general insurance company leading to operational losses. As such, the hybrid modeling approach exhibits an advantage over the standardized approach in that it gives more information about the factors leading to operational losses and how the various operational risks can be mitigated. That added information is very useful to the regulator and the management functions of general insurance companies in Kenya. This is bound to improve the actuarial framework in enterprise risk management for general insurance as a sector.

This study further showed that in spite of the fact that the difference between the operational risk capital estimates computed by both models wasn't very dramatic, the difference of about KES 30 to KES 50 million could prove to be significant for general insurers in Kenya. Adopting hybrid modeling is necessary in the wake of adoption of new guidelines such as IFRS 9 and IFRS 17, which will change how liabilities and assets are accounted for. Hence, general insurance companies will need to be more prudent in the amount of capital they set aside for operational risk in a bid to manage it actively. The regulator could therefore possibly look into standardizing and improving on this hybrid modeling approach to cater for all the insurance companies so as to be able to improve on risk management practice in the country.

CHAPTER 6: LIMITATIONS, RECOMMENDATIONS AND CONCLUSIONS

6.1 Limitations

First and foremost, it is worth noting that while other risks have generalized methods of computing risk capital, operational risk is a subjective risk in the sense that even if general insurance companies in Kenya used a similar business model to operate, various factors would differ such as level of management and staff performance, cases of fraud (and reporting) if any, system operations and even any damage to physical assets which was assumed to be non-existent in the model. As such, should companies adopt the hybrid simulations model, then the results gotten would only be specific to a singular company and that would make industry-wide analysis by the regulator difficult.

The reluctance of general insurers to provide operational loss data was a fairly huge hindrance to the research. Further, because the process of recording operational loss data would be strenuous, many companies have not yet adopted the practice actively even though they know that it can be a useful and prudent measure of operational risk. As such, the model in the case of this research mostly used scenario analysis and simulation to come up with results. If there were any available operational data to input, more impactful conclusions would have been drawn. It is also worth noting that managing an operational risk database was considered to be very costly by many insurance companies.

The simulations of operational losses yielded by the model may not have included all the necessary risk categories as per Basel II given the assumptions of the model. Therefore, the results of the model cannot be considered to be fully conclusive since various general insurers have various risk categories that are dominant in their operations.

Lastly, the model also failed to incorporate real life scenarios such as the failure of reinsurers to respond to large claims even though such incidences have a low probability of occurrence. However, the research results are deemed to be indicative of what would be the case should general insurers in Kenya adopt a hybrid simulations model.

6.2 Recommendations

It is recommended that should the model be adopted by general insurance companies, financial statements be input and modeled from 2014 when the risk based capital regime was promulgated and then possible forecasts be created to be able to compare with the estimate gotten using the method by the regulator. Further adjustments to the model would be in the process workflow assumptions such as how much capital has been invested, the writing of new policies and policy rates as well as the level of automation in a business.

The methodology used in this study could possibly be applied to life and health insurance companies as well. The complexity of systems and operations varies from that of general insurance companies and as such should be investigated and adjusted accordingly before implementation.

Lastly, since the process is iterative in nature, further study should be done to see how the model can be improved in the coming years as well as how it should be adjusted to ensure it shows a holistic approach into the risk categories that would be necessary for modeling operational risk capital.

6.3 Conclusion

It can be concluded that with the given assumptions of the model and how the model was designed and run, the results can be considered to be indicative of the general insurance industry in Kenya. A hybrid simulations approach should be considered as a better approach for insurance companies in Kenya to use when coming up with operational risk capital estimates. The aim of risk management is to quantify, reduce and mitigate risk. This study showed how operational risk could affect a general insurer and hence provide useful information to the management of general insurers to be able to come up with risk management frameworks like the use of the model to come up with the most prudent and fairly accurate measure of operational risk.

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