Research Journal of Finance and Accounting
ISSN 2222-1697 (Paper) ISSN 2222-2847 (Online)
Vol.12, No.12, 2021 www.iiste.org

Inadequate Insurance Claims Reserving and Financial Distress in Non-Life Insurance Companies in Kenya: A Structural Equation Modeling Approach

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Abstract
Financial distress (FD) is a common occurrence in Kenyan commercial sector and is not lacking in non-life insurance companies in Kenya. Several insurance companies have been placed under statutory management for failure to pay genuine claims and other creditors. Insurance companies provide unique financial services, not only to individuals but also to the growth and development of the economy; giving employment to workers and dividends to investors. Financial distress places insurable properties and businesses at risk thus reducing the general public confidence in the insurance sector. For this paper, the goal was to investigate whether inadequate reserving of claims (IRC) causes financial distress in non-life insurance companies in Kenya. In accounting for insurance claims reserves, increases in reserves mean a reduction of profitability of an insurer, whereas a decrease in reserves increases the profitability resulting in higher taxation and payment of dividends, which drains the insurer's cash flow, thus causing financial distress. Out of 37 non-life insurance companies, registered in 2018 in Kenya, four insurers were subjected to Pilot Testing and another four companies declined to participate in the survey. Secondary data from Insurance Regulatory Authority website was retrieved for calculations of Z-scores as per Altman (1993), amended formula. Primary data was also collected through a questionnaire. A partial least squares Structural Equation Modelling (PLS-SEM) was employed to assess the mediating effect of Insurance Regulatory Association (IRA) supervision on the association between inadequate reserving of claims and financial distress. Goodness-of-fit (GoF) indices were used to assess the model's goodness of fit. By using the discriminative Z-score formula, 52% of the institutions considered in 2018 were financially distressed, compared to 48% in 2017. However, when considering the average of ten years (2009 to 2018), financially distressed companies were 41%. The structural path from IRC to FD was found to be significant at 5% level of significance. Financial Distress (FD) increased with inadequate reserving of claims (IRC) (regression coefficient, = 0.4972, 95% CI (0.315, 0.593). This means that the relationship was significant in thisstudy. In other words, for every unit increase in IRC, FD significantly increased by 0.4972. The indirect effect of IRC on FD via IRA was not significant. Hence, IRA supervision was not a significant mediating factor. In a research in the USA by A. M. Best Company, Inc. (1999), inadequate reserving of claims was identified as a major contributor of failures, accounting for 34%. Managers manipulate claims reserves for several reasons; to please shareholders by paying a good dividend, and to trade-off between managers' personal and corporate goals (Fiordelisi et al., 2013). In Kenya, claims reserving in insurance companies is a top secret only handled by a few top employees. In this research, the findings were that Inadequate Reserving of Claims was significantly correlated to financial distress in non -life insurance companies in Kenya.

Keywords: Non-life insurance companies, Policyholders, Insurance Regulatory Authority, Claims Reserving, Z-Scores, Structural Equation Modelling
DOI: 10.7176/RJFA/12-12-06
Publication date: June 30th 2021

1. Introduction

Globally, there have been waves of failures of insurance companies reported since the 1980s due to financial distress (Brennan & Kraft, 2013). Financial distress is a condition in which companies face financial constraints, making the companies unable to carry out their day to day financial transactions smoothly, for lack of sufficient cash (Altman et al., 2019; Athreya et al., 2019; Dewi & Mahfudz, 2016; Vosoughi et al., 2016). The policyholders' confidence in the insurance business is closely linked to the confidence in the solvency of insurance businesses (Leadbetter & Stodolak, 2009). In fact, financial distress is a financial constraint of an insurer when it is unable to pay its creditors as they fall due. The financial distress of an insurer usually plays out over a period of a long time. Usually during this period of financial distress, regulators have time to intervene in the operations of the company (place the distressed firm under statutory management or receivership) to reduce potential losses to policyholders from the insolvency. Failure of an insurer will not always occur as insurers may linger on, and eventually recover from financial distress through good governance and restructuring (Maroney, 2010).

Financial distress is a common occurrence in Kenyan commercial sector and is not lacking in non-life insurance companies in Kenya (Kihooto et al., 2016; Kimathi & Mungai, 2018; Ntoiti et al., 2017; Ombaba & Kosgei, 2017). In 2018, there were a total of 37 non-life insurance companies underwriting non-life business (Okulo, 2015). For the sake of clarity, Non-Life Insurance business includes all property and liability insurance, an insurance cover running for a period of 12 months. Insurance Claims constitute a major expense of these insurance companies, and these expenses are not known when an insurance company gives insurance covers to customers. In accounting of claims reserves in insurance companies, increases in reserves translates into increases of expenses thus reducing profits whilst decrease of reserves gives higher profits to the company. When a claim is reported by a policyholder, some details of the claim may not be available to the insurance company to assess the cost of the claim. The insurer therefore estimates the cost of the claim in the books of accounts with an anticipation of getting more information to determine the cost. The estimates in the books may either be adequate or inadequate and this depends on the information available to the company.

Some of other factors associated with financial distress include: poor liquidity management; under - pricing and fraudulent claims; a high tolerance for investment risk; management and governance issues; difficulties related to rapid growth and/or expansion into non-core activities; and Sovereign-related risks (Gebreslassie, 2015; Sharma et al., 2020; Sharpe & Stadnik, 2007; Shinong & Zhiwang, 2005). The theoretical foundation of this study is the Agency Theory, as it applies to the Financial Management non-life insurance companies

(Jensen & Meckling, 1979; McColgan, 2001). The shareholders who are the owners of an insurance company run the company by appointing agents, the directors, and managers. The management may not run the companies to the interests of owners, and this may trigger in conflicts between the owners and management. The management is privy to pieces of information that are not ordinarily av ailable to the shareholders. In the course of running the organization, managers may take decisions which are primarily of self-interest and not for the good of the owners of the firm (Mitnick, 2006). In this study, the overall performance of a firm, through the efficient administration of the claims reserving and maintenance, entirely depended on the trustworthy and capability of the agents of shareholders (Teeboom, 2018). Failures of insurance firms are largely attributed to various management factors of which inadequate reserving of claims is a significant variable (Standard and Poor's Rating Services, 2013). In Kenya, a number of insurance companies have been placed under statutory management for failure to pay genuine claims and their creditors (Cheluget, 2014).

2. Literature Review

Several articles in the literature have investigated the reason why non-life insurance companies manipulate loss reserves (Ajemunigbohun et al., 2019; England et al., 2019). The results of these studies suggest a significant manipulation of loss reserves by non-life insurance companies (Fiordelisi et al., 2013). The incentive to overestimate the loss reserve is higher when there is a greater potential for tax savings; insurers manage the loss reserve in an attempt to stabilize earnings; and financially weak insurers are more likely to underestimate their loss reserves. Managers who derive a large portion of total compensation from stocks and options are more inclined to overestimate the loss reserves, to shift earnings to future when stock options are exercised. In an effort to streamline the reserving of claims of non-life insurance business in Kenya, the Insurance Regulatory Authority (IRA) issued guidelines to be followed by the industry with effect from 1st July 2013. Reserving in respect of outstanding and reported claims shall be determined prudently by using case estimate method, average cost per claim method or other recognized method by IRA. The guidelines further provided that reserving in respect of IBNRs shall be valued and determined prudently by using at least two of the following methods in accordance with the risk nature distribution and experiential data of insurance lines: claim-ladder method, average cost per claim method, Bornhuetter-Ferguson method and Standard Development Method. The guidelines gave wide alternatives of determining the reserves, including appointing actuaries to confirm compilation of figures at end of financial years of individual insurers (Weke & Ratemo, 2013).

Studies within the Kenya context have found that the minimum IBNRs mandated by IRA understates reserves of a company according to actuarial alternative methods used (Collins, 2013). The results of the study further suggest that in mandating the minimum IBNRs, the regulator does not necessarily ensure adequate reserves overall and further, there is no proper supervision by IRA. The lack of supervision means insurers can circumvent the system by setting outstanding reserves lower than provided in the guidelines. These results were considered within the context of Kenyan environment, which largely lacks the actuarial experience (Collins, 2013).

3. Methodology

3.1 Study population

Out of a target population of 37 non-life insurance companies, registered as at 31st December, 2018, four insurers were used for pilot survey and another four declined to participate in the survey, only leaving 29 insurers for consideration in the data analysis. For purposes of maintaining confidentiality, we ensured that the names of the insurance companies were not shown. To meet the objective of this study, data was collected both from the primary source using a semi-structured questionnaire, as well as from the secondary source (Insurance Regulatory Authority website) relating to 2018 financial accounts.

3.2 Data Collection

3.2.1 Secondary Data

Secondary data from financial statements posted by the IRA for all non-life insurance companies for the period 2009 to 2018 were used for the calculation of Z-scores, using a formula applicable to private general firms, in predicting the financial distress. Financial distress was calculated on the Altman Z-score that combines common financial ratios to determine likelihood of financial distress leading to bankruptcy or failure of business (Altman & Hotchkiss, 1993). For non-manufacturing companies (both public and private), we used the following formula:

$$Z = 6.56x_1 + 3.26x_2 + 6.72x_3 + 1.05x_4$$

Where; x_1 is working capital ratio

x_2 is retained earnings ratio

x_3 is EBIT (earnings before interest & taxes) ratio, all expressed as a percentage of total assets

and x_4 is book value Equity ratio expressed as a percentage of total liabilities.

In this study, the calculated Z-scores were averaged for each company for the 10 years (2009 to 2018). Companies were classified based on the following criteria: a Z-score of at least 2.60 indicates the bankruptcy was not likely; a score between 1.10 and 2.60 indicates a grey area; and a score of less than 1.10 indicates that bankruptcy was most likely. We dichotomized our outcome variable, Financial Distress, so that non-life insurance companies with average Z-scores below 1.10 were classified as distressed and those above were not classified. In Table 1 below, non-life insurance companies in Kenya were distressed, accounting for 38%. The names of the insurers have been hidden in this study and only given numbers.

Table 1: Averaged Z-sores for the financially Distressed Companies

Insurer's Serial No	2018	2017	Average for 10 years
1	0.3215	0.4428	0.6227
3	1.0948	1.0928	0.9608
5	0.6241	0.8042	1.0751
6	0.7586	0.1505	0.8128
9	0.6228	0.9091	0.8156
10	0.0175	1.2896	1.3140
11	1.2612	1.0995	1.0931
12	1.1427	0.9992	0.9370
13	-0.0286	-0.1066	0.1921
14	1.1145	1.0238	0.9822
15	0.7298	0.6207	1.0330
16	1.0572	1.0148	1591.9
18	0.8868	1.1330	1.3494
19	0.5820	1.2723	1.2144
22	-0.3152	-0.4430	0.1667
23	0.9885	0.6405	1.1999
24	0.5892	0.7859	1.2043
28	1.0977	1.5576	1.2639

3.2.2. Primary Data

As financial statements are only historical, a survey of the possible determinants of financial distress from non-life insurance companies was carried out to validate findings from the analysis of financial statements. Primary data was collected from 29 non-life insurance companies using a semi-structured questionnaire (with both closed and open questions, and statements). The respondents rated items (F_1-F_6, B_1-B_6, E_1-E_6) on a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The rest of the items were factors and were transformed to numeric with labels ranging from 1 to 2 for F_9, 1-3 for B_7, and 1-4 for F_7.

Table 2: Latent variables and their identifiers

Latent variables	Identifiers (Indicators)	
Financial Distress (FD)	F_1	The claims liabilities plus long-term loans are less than Shareholders' funds of the company
	F_2	The total current assets are more than total fixed assets
	F_3	The 2016-end year net profits after tax plus 10% is equal to ordinary shareholders' funds
	F_4	The combined ratio (incurred claims, expenses, and net commissions) is less than 100% of net Earned Premiums.
	F_5	The net profit margin (excluding investment income) for the company has been increasing
	F_6	The company has adequate reinsurance arrangements with reputable reinsurers
	F_7	How long does the company take to settle its creditors, including claims?
	F_9	Without interest income the company will be unprofitable (Yes or No)
Inadequate reserving of Claims (IRC)	B1	The management reviews list of outstanding claims yearly and adjusts claims provisions downwards.
	B_2	The actual amount paid of a claim is equal to reserved provisions previously made
	B_3	The claims paid in current year for IBNRs are more than the IBNR provisions in previous year
	B_4	The insurer strictly uses IBNR reserving rates advised by IRA, in June, 2013
	B_5	The company does not have problems with auditors on reserving of claims
	B_6	The company is satisfied with the overall reserving of Claims
	B_7	Does the claims reserving experience of the company show that the company has been (Over reserving, under reserving or correct reserving)?
IRA Supervision	E_1	IRA thoroughly checks reports submitted to them as per the Act and raises queries in writing
	E_2	IRA makes frequent supervisory visits to your offices, at least once a year
	E_3	IRA ensures compliance of Insurance Act provisions and other guidelines to the letter
	E_4	IRA makes some concerted efforts to save insurers from collapse before placing them under statutory management
	E_5	IRA uses a known performance checklist before placing an Insurer under statutory management
	E_6	IRA discusses proposed amendments of the Act with insurers before it becomes law.

3.2.3 Structural Equation Modelling (SEM)

The aim of this study is to investigate whether inadequate reserving of claims causes financial distress in non-life insurance companies in Kenya, adjusting for the impact of Insurance regulatory authority supervision. To examine the strength of influence of inadequate reserving of claims (IRC) on Financial Distress (FD) in the presence of a mediator variable "IRA supervision" (IRA), we employed partial least squares structural equation modelling (PLS-SEM).

According to Narayanan (2012), "Structural Equation Modelling (SEM) is a flexible class of models that allows for modelling complex relationships between variables that are either observed (manifest variables) or unobserved (latent variables)". SEMs can be thought to be a combination of regression models (called structural models) and factor analysis models (called measurement models). PLS-SEMs consist of three namely the measurement model, structural model, and weighting scheme. Whereas the measurement and structural models are components common in all types of SEMs with latent constructs, the weighting scheme is only found in PLS-SEMs (Monecke & Leisch, 2012). In PLS-SEM, ellipses represent latent variables (LVs), and boxes represent manifest variables (MVs). The different between the covariance-based SEMs and PLS-SEMs is that in PLS-SEMs, each MV is only allowed to connect to one LV. Additionally, all arrows that connect a LV to its block of MVs is supposed to be pointing to the same direction. The connection between MVs and LVs is called measurement or outer model. SEMs do not establish causality, but rather test hypothesized (proposed) relationships between the variables under study (Freedman, 1987; Narayanan, 2012). In our PLS-SEM approach, we allow for the mode A model, called reflective framework, where the arrows point outwards (from LVs to the MVs) (Monecke & Leisch, 2012). Within our PLS framework, one MV is only related to one LV.

4. Findings and Discussions

4.1 Statistical Analyses

First, frequencies and percentages were calculated for the total sample and for subgroups. Second, the researchers used Partial Least Squares SEM (PLS-SEM) to affirm the stated hypotheses and test whether our theoretical framework (Figure 1) was supported by the primary data collected from non-life insurers in Kenya. Data was managed, cleaned, recoded, and analyzed with RStudio (R Core Team, 2020). All descriptive analyses were done using RStudio. Missing data imputation (mean value imputation for numeric data, and mode imputation for categorical variables) was carried out in XLSTAT (Version 2020.3.1 Build 21), an add-in in Microsoft Excel 16, before exporting the imputed data to RStudio for modelling. All modelling was done using RStudio. The researchers developed three latent variables using the block of Manifest Variables (MVs) related to each Latent Variable(LV, in a reflective way), and tested the measurement model using sempls function in semPLS package in RStudio (Monecke & Leisch, 2012, 2012).

The PLS-SEM approach does not permit free intercorrelation between latent constructs in the measurement model, contrary to CB-SEM which allows for free intercorrelations among latent constructs. According to Monecke & Leisch (2012), PLS-SEM is an alternative approach to CB-SEM, and is best suited for events when data is non-normal. PLS-SEMs, also called soft-modelling techniques, are distribution-free and have minimum demands concerning measurement scales, residual distributions, and sample sizes. These minimum demands were the reasons behind our choice of PLS-SEM over CB-SEM. The rule of thumb for sample size required in CB-SEM approach causes the researchers to go for PLS-SEM, which is best suited for small samples ($n = 173$ in this study). To adjust for the impact of IRA supervision, indicators for the IRA latent mediator were included in the measurement model to cater for the mediating/indirect effect. Hoyle (2012, p. 418) defines that a "mediator," or "mediating variable" "as a third variable that intervenes in the relation between an independent variable and a dependent variable, transmitting the effect of the independent variable on the dependent variable.". Mediators are often referred to as "intermediate" or "intervening" variables, which reflect that these variables come between a dependent (endogenous) and an independent (exogenous) variable. We carried out the PLS-SEM in the following steps:

1. The Path Model examines the association between Inadequate Reserving of Claims (IRC) and Financial Distress (FD) and
2. The Path Model examines the mediating effect of IRA supervision (IRA) on the association between Inadequate Reserving of Claims (IRC) and FD.

This model is summarized in Figure 1 below, which represents a hypothesized diagram of mediating/indirect effect of IRA supervision. This is in accordance with suggestions by Thakkar (2020, p. 97).

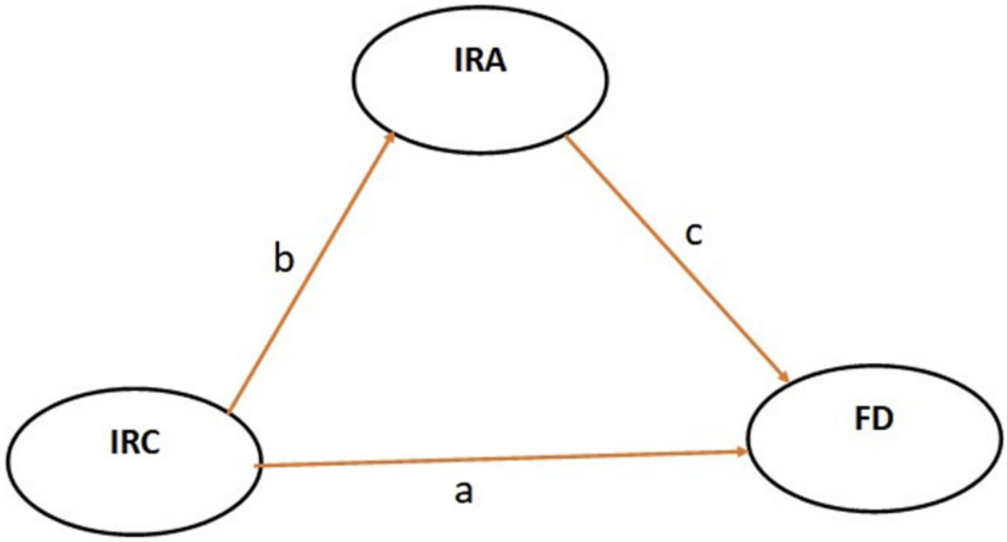

Figure 1: The Postulated Structural Model

In this postulated model a, b and c are paths connecting Latent Variables (LVs), in which Inadequate Reserving of Claims (IRC) has a direct correlation with the Financial Distress (FD) as well as indirect correlation through IRA supervision (IRA), and IRA has a direct effect on the FD. The problem is to analyse whether this conceptual/theoretical model is accurate or not, as well as modifying the system so that the conceptual model is apt for the purpose of drawing conclusions.

4.2 Hypotheses
The following hypotheses were therefore postulated:
Ho1: There is no significant relationship between inadequate reserving of claims and financial distress in non-life insurance companies in Kenya.
Ho2: There is no significant relationship between inadequate reserving of claims and IRA supervision
Ho3: IRA's supervision role is not a significant mediating factor of financial distress in non-life insurance companies in Kenya.
The PLS-SEM algorithm
To test the hypotheses above, the following partial least squares PLS- SEM algorithm was adopted from Monecke and Leisch (2012). The aim of the PLS algorithm was to estimate the values of Latent Variables (LVs in Table 1), called factor scores, by an iterative process. Figure 2 demonstrates the algorithm.

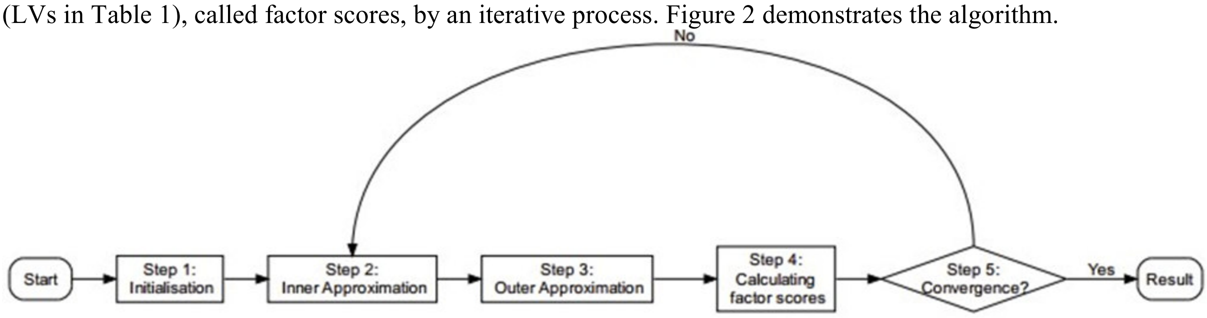

Figure 2: Flowchart for the PLS-SEM algorithm. Source: Monecke & Leisch (2012)

The idea behind PLS-SEM algorithm was to first construct the LVs by the sum of their individual MVs (see Table 1 for MVs or indicators). Then in step 2, the researchers tried to reconstruct each LV using its neighbouring LVs. In step 3, the researchers tried to find the best linear combination of MVs to express each LV, where the coefficients were referred to as outer weights. Finally, in calculating factor scores, each LV was constructed as a linear combination or weighted sum of its MVs. After each step, the LVs were scaled to have a unit variance and zero mean. The algorithm was assumed to stop if the relative change associated with the outer weights was smaller than a predefined tolerance. Missing data were handled by mean value imputation for numeric data, and mode imputation for categorical variables, which replaces the missing values with the mode of non-missing values.

4.3 Parameter Estimation
The plsm function in the "semPLS" R package was first used to create an object suitable for use in the sempls function. The plsm function requires the following input functions: data, strucmod, and measuremod. Data is the dataset to be used in fitting the model, strucmod is a from-to-matrix, which represents the structural model, whereas measuremod is a from-to-matrix, which represents the measurement model. Once the model was set up using plsm function, model parameters were then estimated using the sempls function. The fitted PLS-SEM model was fitted using the imputed data

(n : : 173) with a tolerance of 10^{-7}, which specified the tolerance for the maximum relative difference between the outer weights from one iteration to the following one. Our model converged after 18 iterations. For significance testing of path estimates (loadings and path coefficients), bootstrap resampling with 500 resamples was used throughout this study. The boot package in RStudio was used to compute the standard errors and 95% confidence intervals for the path estimates.

4.3.1 Tests of Significance of the Parameters and Effects
For significance testing of path estimates (loadings and path coefficients), bootstrap resampling with 500 resamples was used throughout this study. The boot package in RStudio was used to compute the standard errors and 95% confidence intervals for the path estimates.

To get the indirect effects from the output generated using the bootsempls function in the R boot package, the direct effects (loadings and path coefficients) related to each variable were multiplied. For example, the indirect effect of IRC on FD was computed by multiplying the path coefficients for paths and (see Figure 1 for postulated the paths). This calculation is in accordance with the proposed formula by Monecke & Leisch (2012) and Nitzl et al. (2016). To test the significance of indirect effects, the procedures described in Hair et al (2016), Carrión et al. (2017) and Nitzl et al. (2016) were employed. According to Carrión et al. (2017), the strength of the indirect effect determines the mediation size. Therefore, a significant mediating (indirect effect) is the only pre-requisite for establishing an indirect effect. Bootstrap tests are employed to test the significance of mediating effects.

The bootstrap results for the mediating effect of IRA supervision were carried out in an Excel spreadsheet. First, the output of the original path coefficients and the 500 bootstrap sub-samples for indirect path (paths b, c) were exported from R to an Excel sheet. Second, the results of the path coefficients for paths b and c were multiplied to get the product terms $b \times c$ in new columns. In the third step, the mean values of the 500 sub-samples for the indirect path were calculated using the function **AVERAGE (array** in Excel. 95% confidence intervals were then calculated for the indirect effect $b \times c$ as follows:

i. The researcher selected an alpha error as $\alpha/2 = 0.025$ at each tail since a two-sided test was being conducted.

ii. The lower and upper bounds of the 95% confidence interval for $b \times c$, were as $n \times (0.5 \pm 95\%/2)$th ordinal position of the ordinal list. In other words, since $n = 500$ in this study, the lower bound can be found in the $500 \times (0.5 - 0.95/2) = 12.5$th ordinal position.

iii. The lower and upper bounds, at the 95% confidence interval, were computed using the function **PERCENTILE (array, k)** in Excel.

iv. Then the confidence interval was bias corrected by adding the bias (that is, original path coefficient − mean of the nth bootstrap sample) to $n \times (0.5 \pm 95\%/2)$th. For instance, the bias-corrected 95% confidence interval for the indirect effect $b \times c$ was computed as:

$$500 \times (0.5 \pm 95\%/2)\text{th} + Bias(b \times c) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

If zero was not included in the confidence interval, then the researcher assumed that there was a significant indirect effect $b \times c$

4.3.2. The weighting schemes

It is used to estimate the inner weights in Step 2 (Figure 2) of the algorithm. There are three weighting schemes that are available namely, the centroid, path, and factorial weighting schemes. For each weighting scheme, the LVs are constructed as weighted sums of the LVs they are related with. The difference in the weighting schemes is brought by the manner in which relation is defined. In general, the researchers expressed the inner estimate as a matrix product of the matrix of inner weights and the outer estimate (Monecke & Leisch, 2012). In this study, we used the path weighting scheme (or structural scheme), where the successor (out-neighbourhood) and the predecessors (in-neighbourhood) of a LV play a distinct role in the relation. In this set up, the relation for a LV with its successor is determined by the correlation between them, whereas for the predecessors, such relation is determined by multiple regression (Monecke & Leisch, 2012, 2012). By specifying the path weighting scheme using the argument weight= 'pathWeighting', we computed the inner weights, used to determine the relation between LVs.

Calculation of path coefficients, loadings, and total effects

Once the factor scores were estimated using the PLS-SEM algorithm, the path coefficients for the structural model were estimated using ordinary least squares (OLS). For each LV, the path coefficient was simply the regression coefficient on its predecessor (other LVs). The estimated matrix of the path coefficients is the transition matrix for the inner or structural model. The matrix of total effects was calculated as the sum of the elements of the transition matrices. The researchers then squared the elements of the transition matrix to get the indirect effects mediated by only one latent variable (in this case, IRA supervision). Path coefficients and total effects were extracted using pathCoeff() and totalEffects() functions.

Criteria for Model validation

To validate the fitted model, the following goodness-of-fit indices (Table 3) were used, available in the semPLS package (Monecke & Leisch, 2012).

Table 3: Criteria for Model Validation available in the semPLS R package

Function	Model criteria
rSquared( )	R^2 values, coefficients of determination for each endogenous LV
dgrho( )	Dillon-Goldstein's ρ, also called composite reliability
redundancy( )	Redundancy indices for the endogenous LVs
communality( )	Communality indices for LVs measured reflectively with more than MV
gof( )	Good-of-Fit (GoF) index, the geometric mean of the average communality, and average determination coefficient.

4.4 Results of the Study

4.4.1 Characteristics of the Non-life Insurance companies considered

Out of 29 non-life insurance companies considered in 2018, and using the discriminative Z-score formula, 52% were found to be financially distressed, compared to 48% in 2017. Out of 14 companies spotted as financially distressed in 2017, four (29%) companies had become worse; ratios deteriorating in 2018, and only one company showed signs of improvement. On average, 38%% of the non-life insurers in Kenya were financially distressed (Table 1).

4.4.2 Demographic Characteristics of respondents

The demographic characteristics and behaviours of the respondents reveal that 65.8% of the respondents were males, while 34.2% were females. 46.8% of the respondents were from the management, while the rest (53.2%) belonged to other cadres. 60.7% of the respondents were graduates, 29.8% were post-graduates, while 7.1% were diploma holders. 65.7% had served in their current companies for a period of 0 to 5 years, 23.8% had served between 6 and 10 years, 4.7% had served between 11 and 15 years, and only 5.8% had served in their current insurers for more than 16 years.

4.4.3 Responses of Indicators to Inadequate Reserving of Claims

Under Table 4, most of the study participants agreed that the management reviews list of outstanding claims yearly and adjusts claims provisions downwards. On the actual amount paid of a claim being equal to reserved provisions previously made, there was a split response. There was also a split confirming on whether IBNR provisions were adequate or not. Most of the respondents confirmed that the insurer strictly uses IBNR reserving rates advised by IRA, in June 2013. A high percentage agreed that the external auditors did not qualify accounts on account of reserving of claims. On other responses (indicators B7 and B8, and not in Table 4), the respondents confirmed that 6.8% of insurers had been over reserving, while 66.7% and 26.5% confirmed that reserves were correctly stated, and under reserved, respectively.

Table 4: Summary of Responses on Inadequate Reserving of Claims

Indictors	Respondents	disagree	Strongly Disagree	Total disagree	Agree	Strongly agree	Total Agree
B1	170	4.7%	15.3%	**20%**	44.1%	25. 9%	**70%**
B2	170	4.1%	40.6%	**44.7%**	33.4%	10.6%	**43%**
B3	168	5.4%	26.2%	**31.6%**	28.6%	4.8%	**33.4%**
B4	169	1.8%	10.1%	**11.9%**	41.4%	27.2%	**68.6%**
B5	168	1.2%	10.7%	**11.9%**	48.8%	28.6%	**77.4%**
B6	167	12.6%	7.2%	**19.8%**	55.1%	25%	**80.2%**

4.4.4 Responses to Indicators of IRA Supervision

Table 5, most of the respondents tended to agree that the IRA thoroughly checks reports submitted to them as per the insurance Act, 487. A higher percentage of the respondents agreed that the IRA makes frequent supervisory visits to insurers' offices, and most of respondents also agreed that IRA ensures that compliance of insurance Act by the industry provisions. Most of the respondents said that IRA makes some concerted efforts to save insurers from collapse before placing them under statutory management. A higher percentage of the respondents confirmed that IRA does not use a known performance checklist before placing an Insurer under statutory management. However, a good number of the respondents agreed that IRA discusses proposed amendments to the Act with insurers before it becomes law. On statements not covered in Table 5, most of the respondents confirmed that less than 5% companies had been saved from collapse by IRA in the last 10 years, and less that 5% had been placed under statutory management.

Table 5: Summary of responses on Supervision by IRA

Indicators	Respondent	Strongly disagree	Disagree	Total Disagree	Agree	Strongly agree	Total Agree
E_1	173	Nil	4.6%	**4.6%**	4.6%	56.6%	**87.2%**
E_2	173	1.7%	7.5%	**9.2%**	61.2%	16.8%	**88.1%**
E_3	173	2.9%	13.3%	**16.2%**	54.3%	20.8%	**75.1%**
E_4	173	2.3%	8.1%	**10.4%**	54.9%	12.1%	**67.0%**
E_5	172	1.2%	4.1%	**5.3%**	47.7%	11%	**58.7%**
E6	171	1.2	7%	**8.2%**	58.5%	12.9%	**71.4%**

4.4.5 Responses to Financial Distress Indicators

Table 6, a good percentage of the respondents agreed the claims liabilities plus long-term loans are less than Shareholders' funds of the company. A small percentage of the respondents confirmed that some companies are operating with negative shareholders' equity. A good percentage agreed that the combined ratio (incurred claims, expenses, and net commissions) is less than 100% of net earned premiums for 2018 whilst a substantial percentage disagreed. There was a split response that the net profit margin (excluding investment income) for the company has been increasing, suggesting that several companies were making losses thus tending to be financially distressed agreeing to the Z-score calculations, giving a prediction of 52% of distressed companies. Most of the respondents agreed that the companies had adequate reinsurance arrangements with reputable reinsurers. When asked about how long the company takes to settle its creditors, including claims, majority said that the company takes 30 to 60 days (43%), while 29.7% said that the company settles its creditors within 30 days. 15.1% and 12.2 % said that the companies take over 90 days and 60 to 90 days to settle creditors, respectively.

Table 6: Summary of Responses on Measures of Financial Distress

Indictors	Respondents	Strongly Disagree	Disagree	Total Disagree	Agree	Strongly Agree	Total Agree
F1	166	7.8%	21.7%	**29.5%**	36.1%	15.1%	**51.2%**
F2	167	5.4%	33.5%	**38.9%**	22.2%	15.0%	**37.2%**
F3	164	9.1%	38.4%	**47.5%**	11.6%	3.7%	**15.3%**
F4	164	2.4%	25.6%	**28.0%**	36.0%	11.6%	**47.6%**
F5	168	3.6%	34.5%	**38.1%**	35.1%	13.2%	**48.3%**
F6	168	4.2%	3.0%	**7.2%**	52.7%	40.0%	**92.7%**

4.4.6 Results from Structural Equation Modelling

Parameter Estimation

For significance testing of path estimates (loadings and path coefficients), we used 500 bootstrap samples, and used them to initialize the outer weights. We obtained the bootstrap confidence intervals using the method of generating confidence intervals by DiCiccio and Efron (1996), which leads to more accurate coverage rates in the event that the distribution of bootstrap draws is not normal as per Table 7. The structural path from IRC to FD was therefore found to be significant at 5% level of significance. The second column shows the mean of the parameters obtained from the 500 bootstrap samples. The third column represents the bias, and the fourth displays the standard errors (deviation of these estimates around their respective means). The last two columns give the lower and upper limits of the 95% bootstrap confidence interval. Table 7 also represents the regression results of financial distress (FD) on the inadequate reserving of claims (IRC), and IRA supervision (IRA). The structural path from IRC to FD was found to be significant at 5% level of significance. Financial Distress (FD) increased with inadequate reserving of claims (IRC) giving a regression coefficient, = 0.4972, at 95% CI (0.315, 0.593). This relationship was significant. In other words, for every unit increase in IRC, FD significantly increased by 0.4972.

Table 7: Bootstrap Estimates, Standard errors, and 95% Confidence Intervals for the Path Estimates

	1	2	3	4	5	
Path	Estimate	Mean bootstrap Estimate	Bias	Standard Error	95% bca confidence interval	
Outer model					Lower	Upper
IRC -> B1	0.18969	0.20012	0.00591	0.136	-0.070	0.453
IRC -> B2	0.40150	0.38612	-0.00949	0.108	0.176	0.607
IRC -> B3	0.41647	0.40112	-0.01246	0.112	0.171	0.612
IRC -> B4	0.59736	0.60065	-0.00082	0.090	0.367	0.742
IRC -> B5	0.81205	0.80667	-0.00575	0.040	0.720	0.879
IRC -> B6	0.79494	0.78903	-0.00754	0.039	0.705	0.851
IRC -> B7	0.61499	0.60222	-0.00516	0.075	0.446	0.734
IRA -> E1	0.83671	0.80744	-0.03037	0.084	0.760	0.909
IRA -> E2	0.75773	0.73522	-0.02880	0.102	0.567	0.874
IRA -> E3	0.74122	0.70127	-0.03443	0.147	0.155	0.858
IRA -> E4	0.55577	0.50743	-0.03474	0.185	-0.090	0.745
IRA -> E5	0.57999	0.53505	-0.03644	0.171	-0.034	0.750
IRA -> E6	0.18838	0.14236	-0.02713	0.216	-0.331	0.514
FD -> F1	0.40660	0.40185	-0.00341	0.116	0.141	0.609
FD -> F2	0.56962	0.55835	-0.00495	0.079	0.375	0.698
FD -> F3	0.23062	0.21639	-0.01119	0.150	-0.062	0.514
FD -> F4	0.28430	0.27164	-0.01433	0.132	0.012	0.510
FD -> F5	0.67253	0.66101	-0.01210	0.072	0.495	0.775
FD -> F6	0.67973	0.67185	-0.01011	0.064	0.523	0.779
FD -> F7	0.75493	0.74069	-0.01502	0.057	0.633	0.840
FD -> F9	0.32237	0.31306	-0.00721	0.116	0.048	0.504
Inner model						
IRC -> IRA	0.34088	0.36845	0.02164	0.087	-0.034	0.460
IRC -> FD*	0.49717	0.51970	0.02267	0.063	0.315	0.593
IRA -> FD	0.06721	0.07456	0.01093	0.092	-0.146	0.221

*Significant at

The table of effects contains the effects that each LV has on the rest of LVs by taking into consideration the total number of paths/ connections in the structural (inner) model (Sanchez, 2013). The direct effects are usually given by the path coefficients, as can be seen in Table (path coefficients). But there are also the indirect and total effects. An indirect effect can be termed as the influence of one LV on another LV by taking an indirect path. The total effects, thus, are the sum of both the indirect and direct effects. For instance, in Table 8, IRC affect FD both directly, and indirectly through IRA supervision. The indirect effect of IRC on FD via IRA is 0.0229.

Table 8 Total, Direct and Indirect Effects (Path Coefficients)

Paths	Direct	Indirect	Total
IRC -> IRA (**b**)	0.34088	_	0.34088
IRC -> FD (**b via c**)	0.49717	0.0229	0.52007
IRA -> FD (**c**)	0.06721	_	0.06721

Tests of Significance of Mediating (Indirect) Effects

As discussed earlier, mediation can occur when a third latent variable in a model intervenes/ intermediates between two other related latent variables. In other words, a change in the independent variable causes a change in the mediator variable (M), which in turn causes a change in the dependent variable in the PLS-SEM. Hence, the mediator variable (M) governs the nature of relationship between two constructs. To be more precise, IRA supervision is the mediating variable in this study. In this study we investigated whether the indirect effect was significant at level of significance.

Table 9: Summary of Mediating effects Tests

	Coefficient	Bootstrap 95% CI (Bias-corrected)	
Direct effects		**Lower**	**Upper**
B	0.34088	-0.0341	0.460
C	0.06721	-0.1456	0.221
Indirect effects			
$b \times c$	0.0229	-0.0423	0.0820

From Table the indirect effect was not significant at significance level. Hence, Ho3 is supported. The researcher concluded that IRA's supervision role was not a mediating factor of financial distress in non-life insurance companies in Kenya. In other words, IRA supervision does not mediate the relationship between inadequate reserving of claims (IRC) and financial distress (FD). However, the direct effect of IRC on FD (path a) proved significant. This means that hypotheses Ho1 is not supported. That is, there is a significant relationship between inadequate reserving of claims and financial distress in non-life insurance companies in Kenya.

4.6 Model evaluation of the Measurement model

The fit measures suggested a good model fit as shown by the actual values against the preferred values as per Table 7. The results of the PLS-SEM model, using structural model path weighting scheme, show a moderate R-square value of 0.30 for Financial Distress, and a weak level of 0.12 for IRA supervision as per Table 9.

4.6.1 Assessment of the Block Unidimensionality

The measurement model for each block of MVs is a reflective one. The statistics for checking unidimensionality of each block are given in Table 10. All the values of Dillon-Goldstein's values lead to acceptance of unidimensionality of all blocks, thus supporting homogeneity of the indicators.

Table 10: Dimensionality Indices

Block	Number of MVs	Dillon-Goldstein's ρ	Preferred value	Conclusion
IRC	7	0.76	>0.7	Good fit
IRA	6	0.79	>0.7	Good fit
FD	8	0.73	>0.7	Good fit

4.6.2 Discriminant validity of the Measurement model

Quality of the measurement model was also examined by checking discriminant validity of the loadings and path coefficients (Monecke & Leisch, 2012). Discriminant validity shows how different a given latent construct is from other latent constructs. Discriminant validity indicates the loyalty of the MVs to their LV, and it can be captured in the cross loadings of the MVs. For discriminant validity to hold, the MVs associ ated with a given LV should be greater than their loading with any other LV. In Table 7, each MV is more correlated to its own LV than to the other LVs. To make the table more readable, the researchers specified the relative difference between the cross and outer loadings to be at which cross loadings were to be printed. All the MVs, therefore, agree with their own LVs, supporting discriminant validity of the LVs.

Table 11: Loadings/ Correlations between MVs and LVs

	IRC	IRA	FD
B1	0.19		0.187
B2	0.401		
B3	0.416		
B4	0.597		
B5	0.812		
B6	0.795		
B7	0.615		
E1		0.837	
E2		0.758	
E3		0.741	
E4		0.556	
E5		0.58	
E6		0.188	
F1			0.407
F2			0.57
F3			0.231
F4			0.284
F5			0.673
F6			0.68
F7			0.755
F9			0.322

4.7 Model evaluation of the Structural model

4.7.1 Structural model path coefficients

As Table 7 shows, only the effect of inadequate reserving of claims (IRC) on financial distress (FD) was statistically significant at 5% significance level (95% CI: (0.315, 0.593)). The pathDiagram() function returns the graphical representation of the hypothesized/ postulated model with loadings and path coefficients. The loadings and path coefficients in Table 7 can be easily be viewed in Figure 3. To check the statistical significance of the regression coefficients, Table 7 should be referred to.

4.7.2 Communality and Redudancy

The communality indices in Table 8 measure the quality of the measurement model for each respective block. Considering the measurement model, the redundancy indices measure the quality of the structural model for each endogenous block (Tenenhaus et al., 2005). Coefficients of determination (R^2 values) indicate the quantity of the variance in the endogenous LVs explained by their exogenous LVs.

Table 12: Coefficients of determination, R^2, Communality and Redundancy

Block	Number of MVs	R^2	Communality	Redundancy
IRC	7		0.34	
IRA	6	0.12	0.42	0.049
FD	8	0.30	0.28	0.076
Average		**0.20**	**0.34**	**0.062**

The coefficient of determination of 30% for financial distress (FD) indicates a moderate level of model fitness. The value means that 30% of the variance in the endogenous variable FD is explained by its exogenous variables IRC and IRA. The communalities (which are squares of the loadings) are below the acceptable 0.50 value. The values of redundancy for the endogenous LVs are somehow low showing that the exogenous LVs explain an infinitesimal amount of variance in the endogenous LVs. Finally, the global criterion of goodness-of-fit, GoF index of 0.26 for the entire model is well below the suggested 0.70 cutoff. The GoF can be called using the function gof() in the “semPLS” R package.

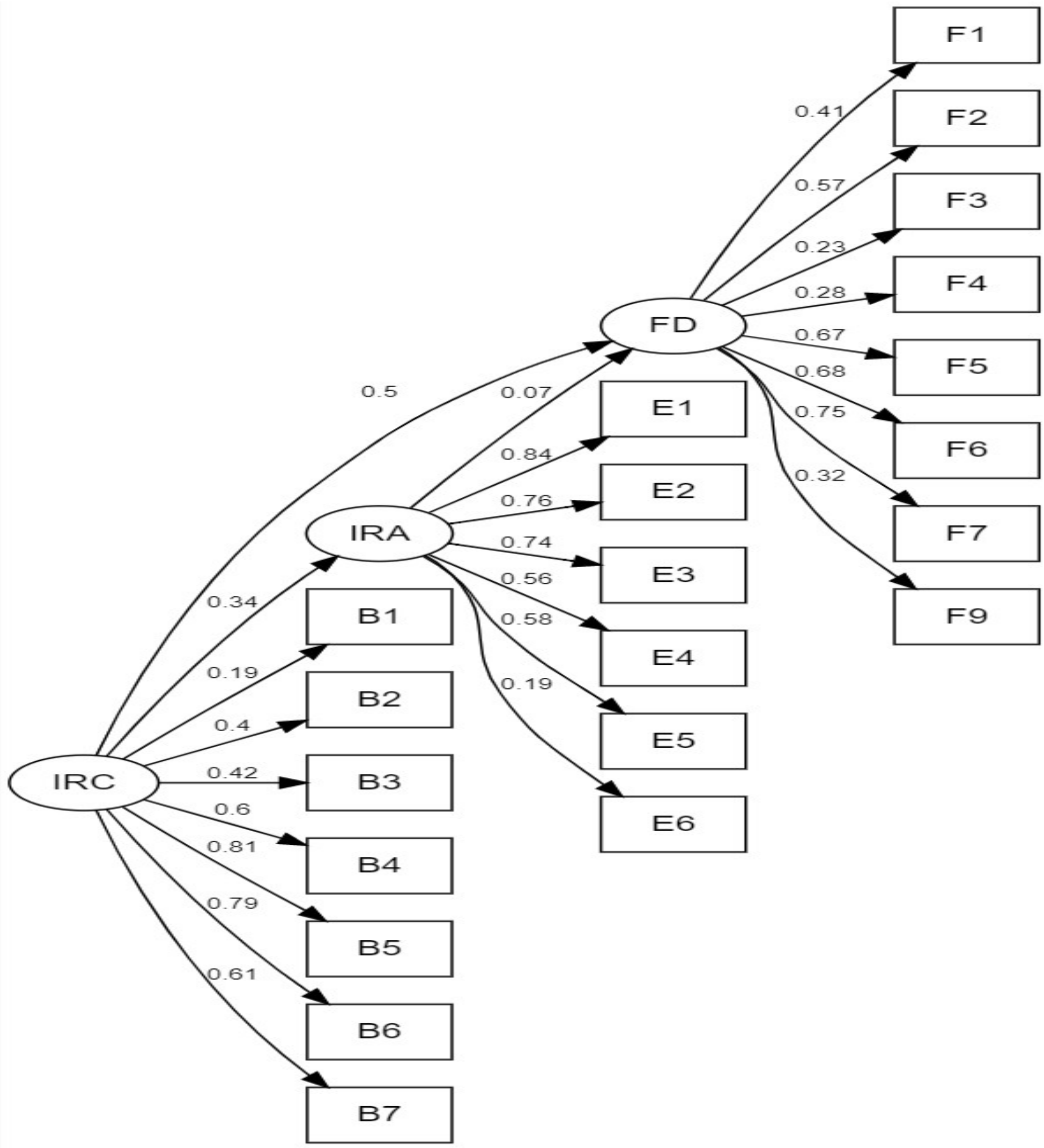

Figure 3: A path diagram for the fitted PLS-SEM model

4.7.3 Hypothesis Testing

As per the initial hypothesized model, there is no relationship between inadequate reserving of claims and financial distress (Ho1), there is no relationship between inadequate reserving of claims and IRA supervision (Ho2), and IRA's supervision role is not a mediating factor of financial distress (Ho3). After the results from PLS-SEM, the confidence intervals for the factor loadings indicate that there is a relationship between inadequate reserving of claims and financial distress (that is, inadequate reserving of claims positively influences financial distress); there is no relationship between inadequate reserving of claims and IRA supervision, and IRA's supervision role is not a mediating factor of financial distress. Since the bootstrap confidence intervals of the of path coefficients include 0 (Except for IRC) on financial distress, 95% CI: 0.315, 0.593), the estimates do not account for large variance, and hence we support the respective hypotheses as per Table 7. Finally, the hypothesis results are as follows:

Ho1: Reject
Ho2: Not reject
Ho3: Not reject

5. Conclusion

This study was to investigate the impact of Inadequate reserving of claims on financial distress in non-life insurance companies in Kenya. We employed a Structural Equation Modelling (SEM) approach to assess these relationships: in which inadequate reserving of claims (IRC) has a direct correlation with the financial distress (FD) as well as indirect correlation through IRA supervision (IRA), and IRA has a direct correlation with FD. The findings of this study suggest that inadequate reserving of claims lead to financial distress in non-life insurance companies. The structural path from IRC to FD was found to be significant at 5% level of significance. Financial distress (FD) increased with inadequate reserving of claims (IRC) with a regression coefficient of = 0.4972, (95% CI (0.315, 0.593)). In other words, for every unit increase in IRC, FD significantly increased by 0.4972. The respondents (26.5%) confirmed from the survey that insurance companies were under reserving claims. This means that managers try to underestimate claims so that companies can post good results (Fiordelisi et al., 2013).

The postulated model in this study did not clearly incorporate all factors that may affect financial distress in non-life insurance companies; only one exogenous variable was considered. Second, the administration of the questionnaire left a lot to be desired in securing the primary data; four companies did not participate in the survey, and employees were reluctant to complete the questionnaire independently for fear of victimization by management. There was therefore a very high percentage (66.7%) who simply reported that there was correct reserving of claims. Third, the prediction model of financial distress, the Altman's Z-score, used this study is applicable to non-manufacturing companies, both public and private, not specifically for insurance companies.

Future studies could address some of this study's limitations. First, more exogenous variables should be included in the studies; effects of management, financial management, fraudulent claims and corruption in the insurance industry, under- pricing of insurance products, unfair competition in the insurance market, lack of innovative abilities to match globalization and upcoming trends insurance needs, particularly in the ever- changing social economical world. Second, completion of questionnaire thus 'drop and pick' is becoming cumbersome. It is recommended that perhaps awaiting method should be adopted, where the researcher awaits as the questionnaire is being completed. This is to avoid unnecessary interference from management. Finally, there is room to come out with a Kenyan model for prediction of financial distress in insurance companies, rather than using the Altman's model. Finally, even though our model fit the data reasonably well, it is possible that other models or configurations would have fit the data equally well or better. Alongside these limitations, this study had several advantages and strengths, so that the findings are an important contribution to understanding that Inadequate Reserving of claims, in insurance industry in Kenya, may not be dismissed. This study was conducted using a small population of 29 insurers with a small sample size of respondents not exceeding 180 with institutionalized adult population and this was processed well with SEM. SEM allowed us to test multiple relationships simultaneously within a postulated conceptual model using one variable. This is important in research where several mediating variables are suspected to have complex inter correlations.

Possible Future Research Directions

The following areas require further research to establish reasons for financial distress in non-life insurance companies in Kenya: first, the effect of the companies' corporate governance; second, the effect of underpricing; third, the effect of inadequate Equity Capital; fourth, the effect of unfair competition; fifth, the effect of investment policies; sixth, and not least, an appropriate predictive model for financial distress in general insurance Business to replace the Altman's Z-score formula.

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