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Risk of Fraudulent Claims 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 fraudulent claims (FC) significantly cause financial distress in non-life insurance companies in Kenya. In accounting for insurance fraudulent claims, increases in fraudulent claims mean a reduction of profitability of an insurer; and payment of fraudulent claims 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 using Altman's [1], amended formula. Using the discriminative Z-score formula, 52% of the non-life insurance companies 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 38%. To confirm this distressful situation, primary data was also collected through a questionnaire. A partial least squares structural equation modelling (PLS-SEM) approach was employed to affirm the researcher's hypotheses and further test whether theoretical framework was supported by primary data analysis. Goodness-of-fit (GoF) indices were used to assess the model's goodness of fit. The structural path from FC to FD was found to be significant at 5% level of significance. Financial Distress (FD) increased with an increase in fraudulent claims (FC) (regression coefficient, β= 0.32, 95% CI = (0.16, 0.4)). This means that the relationship was significant in this study. In other words, for every unit increase in FC, FD significantly increased by 0.32. However, the indirect effect of FC 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 [2], alleged fraud in insurance claims was identified as one of contributors of insurance companies' failure, accounting for 10%. An insurance fraud survey carried out by an audit firm KPMG [3] showed that Kenyans could have paid over Kshs 30 billion to cover for fraud. The researchers further observed that companies' employees were found to be colluding with policyholders and claims agents to doctor and file illegitimate claims with the insurers. The insurance business classes which are most affected by fraud are motor and medical classes. The researchers recommends that members of staff of insurance companies be trained to effectively detect fraudulent claims; and that the insurance act be amended to give power to the board of directors in stamping out of financial distress in the insurance industry.

Keywords: *non-life insurance companies, policyholders, insurance regulatory authority, claims reserving, z-scores, structural equation modelling*

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1. Introduction

Globally, there have been waves of failures of insurance companies reported since the 1980s due to financial distress [4]. Financial distress is a condition in which companies face financial constraints, making the companies unable to carry out day to day financial transactions smoothly, for lack of sufficient cash [1,5,6,7]. The policyholders' confidence in the insurance business is closely linked to the confidence in the solvency of insurance businesses [8]. It 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 either to stabilize operations of financially distressed companies or place the distressed firm under statutory management or receivership to reduce potential losses to policyholders from the insolvency of an insurer. Failure of an insurer will not always occur as insurers may linger on, and eventually recover from financial distress through good governance and restructuring [9].

Financial distress is a common occurrence in Kenyan commercial sector and is not lacking in non-life insurance companies in Kenya [10,11,12]. In 2018, there were a total of 37 non-life insurance companies underwriting non-life business [13]. 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 (including fraudulent 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 for fraudulent claims in insurance companies, increases in fraudulent claims translates into increases of expenses thus reducing profits whilst decrease of fraud cases gives higher profits to the company. When a claim is reported by a policyholder, it may not be known to be fraudulent until the insurer thoroughly investigates the claim. In most cases, fraudulent claims may not be entirely prevented because of members of staff collusion with the perpetrators of fraud.

2. Fraud Theories and Literature Review

In Kenya, a number of insurance companies have been placed under statutory management for failure to pay genuine claims and what is owed to creditors [14]. The Insurance Regulatory Authority (IRA) is mandated to protect the public [15]. However, some of the factors that cause financial distress are many and varied and may include: poor liquidity management; underpricing and inadequate reserving; alleged 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 [16,17,18,19]. The theoretical foundation of this study is the Agency Theory, as it applies to the financial management of non-life insurance companies [20,21]. 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. 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 [22]. In this study, the overall performance of a firm, through the efficient detection of fraudulent, entirely depends on the training, the trustworthy, and capability of employees who are the agents of shareholders [23]. Failures of insurance firms are largely attributed to various management factors of which lack of detection of fraudulent claims is a significant variable [22].

The Fraud Triangle theory [24] is a critical framework for helping companies to focus on prevention and deterrence efforts. Some fraudsters may have a fundamental belief that insurers have lots of money, and deserve a loss. The justification of fraud may therefore take many forms [25]. The author further observes that in most cases, windows of opportunity exist for wrong doing when companies have poor internal controls and lack of management’s review and oversight. The fraudsters knowingly provide false incomplete or misleading information to an insurer for purposes of defrauding, often leading to cash flow problems for affected insurance companies [26].

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, the researchers 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

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 [26]. 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. The researchers dichotomized the 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, 52% non-life insurance companies in Kenya were predicted as financially distressed as 31st December, 2018, compared to 48% in 2017. On the average for 10 years (2009 to 2018) 38% were distressed. The names of the insurers have been hidden in this study and only given numbers.

Table 1. Average Z-scores for the Financially Distressed Insurance Companies [Insurers' Serial No.-A, Average for 10 years-B]

A	2018	2017	B
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

Primary Data: In this study, a survey of the variable, fraudulent claims, was carried out to validate findings from the analysis of secondary data (financial statements), using Altman's Z-score formula. Primary data was collected from 29 non-life insurance companies using a semi-structured questionnaire (with both closed and open questions, and statements). The researchers adopted a mixed research design, considering both quantitative and qualitative data. The respondents rated items (F_1-F_6, C_1-C_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 C7A-C7D and C8A-C8D, and 1-4 for F_7.

3.3. Structural Equation Modeling

The aim of this study was to investigate whether fraudulent claims cause financial distress in non-life insurance companies in Kenya, adjusting for the mediating effect of Insurance regulatory authority (IRA) supervision. To examine the strength of influence of fraudulent claims **(**FC**)** on Financial Distress (FD) in the presence of a mediator variable "IRA supervision" (IRA), the researchers employed partial least squares structural equation modelling (PLS-SEM) approach.

Reference [27], '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 [28]. 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 [28,29]. In this PLS-SEM approach, the researchers used model 1 (reflective framework), where the arrows point outwards from LVs to the MVs, [28]. Within the PLS framework, one MV is only related to one LV.

4. Statistical Analyses

In this study, the researchers calculated frequencies and percentages for the total sample and for subgroups and then used Partial Least Squares SEM (PLS-SEM) approach to affirm the researcher's hypotheses and further test whether the 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 [30]. 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 ***samples*** function in ***semPLS*** package in RStudio (R package semPLS: Available from CRAN R-project website: http://CRAN.R-project.org/package=semPLS [25].

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 reference (28), 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. Reference [31] 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. The researchers carried out the PLS-SEM in the following steps:

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

This model is summarized in Figure 1, which represents a hypothesized diagram of mediating/indirect effect of IRA supervision. This is in accordance with suggestions by [32].

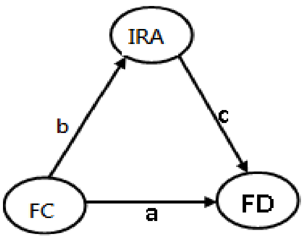

Figure 1. The Postulated Structural Model

In this postulated model a, b and c are paths connecting Latent Variables (LVs), in which Fraudulent Claims (FC) 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 analyze 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.

4.1. Hypotheses

The following hypotheses were therefore postulated:

Ho1: There is no significant effect of fraudulent claims on financial distress in non- life insurance companies in Kenya.

Ho2: There is no significant relationship between fraudulent claims and IRA supervision.

Ho3: There is no significant mediating effect of Insurance Regulatory Authority (IRA) of financial distress in non-life insurance companies in Kenya.

4.2. The PLS-SEM Algorithm

To test the hypotheses above, the following partial least squares PLS- SEM algorithm was adopted from reference [25]. 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 (Start; Step 1- Initialisation; Step 2, Inner Approximation; Step 3, Outer Approximation; Step 4, Calculating Factor scores; Step 5, Convergence; Yes, Result).

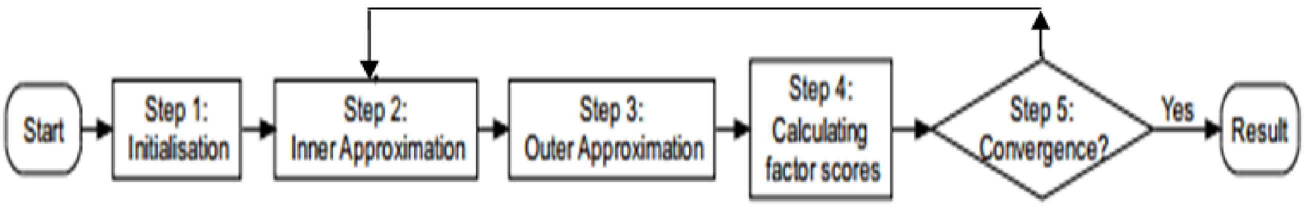

Figure 2. Flowchart for the PLS-SEM algorithm. Source: Monecke & Leisch [29]

The idea behind PLS-SEM algorithm was to first construct the LVs by the sum of their individual MVs (see Table 4 for MVs). Then in step 2, the researchers tried to reconstruct each LV using its neighboring 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 was 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

In fitting the PLS structural equation model into the data, the researcher proceeded as follows:

1. For **Model 1**, 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. The items with negative factor loadings on their respective latent variables had the negative sign reversed (converted to positive) to meet the requirements for reflective model in PLS-SEM. The first model converged after 41 iterations.

2. For **Model 2**, the researcher identified the items (statements/questions) with a factor loading less than 0.7 in model 1. These items were dropped in accordance with Sanchez's proposal [30]. Only those items with factor loadings more than or equal to 0.7 were included in the second model. Model 2 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. The second model converged after 10 iterations. In this study, the researcher presents the results of the items that reflected the latent variables sufficiently i.e., results from model 2. This is for convenience purposes.

4.4. Tests of Significance of the Parameters and Effects

For significance testing of path estimates (loadings and path coefficients) resulting from model 2, 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 FC on FD was computed by multiplying the path coefficients for paths ***b*** and ***c*** (Table 7 for the paths). This calculation is in accordance with the proposed formula by [28] and [34]. To test the significance of indirect effects, the procedures described in [34,35,36] were employed. Reference [36], 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 the 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 $n \times (0.5 \pm ci\%/2)th$ ordinal position of the ordinal list. In other words, since $n = 500$ in this study, the lower bound can be found in the $500 \times (0.5 - 0.95/2) = 12.5th$ 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 $n \times (0.5 \pm ci\%/2)th$. For instance, the bias-corrected ci% confidence interval for the indirect effect $b \times c$ was computed as:

$$500 \times (0.5 - 95\%/2)th + Bias(b \times c)$$

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

4.5. 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 MVs 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 [29]. In this study, the researchers used the path weighting scheme (or structural scheme), where the successor (out-neighborhood) and the predecessors (in-neighborhood) 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 [29]. 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.

Table 2. 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

4.6. Criteria for Model Validation

To validate the fitted model 2, the following goodness-of-fit indices (Table 2) were used, available in the *semPLS* package [26].

4.7. Results of the Study

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, 29% of the 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).

2. Demographic Characteristics of respondents

The demographic characteristics and behaviors 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.

Table 3. Responses to statements/questions in Likert Scale (Latent variables and indicators) [Latent variable-A, Respondents-B, Strongly Disagree-1, Disgree-2, Total Disagree-3, Agree-4, StronglyAgree-5, Total Agree-6]

A	B	1	2	3	4	5	6
		%	%	%	%	%	%
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**	36	11.6	**48.2**
F5	168	3.6	34.5	**40.1**	35.1	13.2	**48.3**
F6	165	N/A	4.2	**4.2**	52.7	40	**92.7**
E1	173	N/ A	4.6	**4.6**	56.6	30.6	**87.2**
E2	173	1.7	7.5	**9.2**	61.3	16.8	**78.1**
E3	173	2.9	13.3	**16.2**	54.3	20.8	**75.1**
E4	173	2.3	8.1	**10.4**	54.9	12.1	**67**
E5	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**
C1	171	N/A	6.4	**6.4**	57.3	32.7	**90**
C2	170	1.8	4.1	**5.9**	56.5	31.2	**87.7**
C3	170	2.9	10	**12.9**	38.8	30	**68.8**
C4	169	3.6	29	**32.6**	37.9	8.3	**46.2**
C5	166	8.4	37.3	**45.7**	36.1	7.8	**44.9**
C6	170	10.6	13.5	**24.1**	40	31.2	**71.2**

The results from the descriptive analyses are displayed in Table 3, which analyses further present the summary of the reactions of respondents to statements/questions in the questionnaire. The indicators are denoted as E for IRA supervision, F for Financial distress and C for fraudulent claims. The respondents largely give some confirmation on the effects of fraudulent claims in insurance companies. Most of the respondents agreed that the insurers had experienced and properly trained staff able to detect fraudulent claims, and a small percentage disagreed with the statement, suggesting that there is no problem with members of staff in detecting fraud. Most of the respondents also agreed that when a suspected fraudulent claim is suspected there is a system of reporting the fraud to management. A small number disagreed that only authorized employees forward the suspected fraud to investigative Fraud Unit in IRA Offices to handle fraud cases whilst most of the respondents agreed. On fraudulent claims do not pass through the systems established without being detected, there was a split response on this matter. Most of the respondents agreed that the cost of fraudulent claims contributed substantially to losses of the insurers. It was further suggested that Fraudulent claims form 10% of the incurred claims, of which motor commercial contributed 45.1% and motor private 64% of the cost.

3. Results from Structural Equation Modelling

Parameter Estimation and Tests of significance

Table 4 represents the factor loadings [of manifest variables (MVs) used to construct the LVs] from model 1 of the PLS-SEM, which converged after 41 iterations. Factor loadings are correlation coefficients between observed variables and latent common factors. The loadings can also be viewed as standardized regression coefficients or regression weights. The researcher considered factor loadings greater than or equal to 0.7 as significant in this survey. In Table 4, items/identifiers with factor loadings greater or equal to 0.7 as significant in this survey.

Table 4. Factor loadings in Model 1

Latent variables to Manifest Variables (Paths)	Factor Loading in Model 1
FC -> C1	0.7
FC -> C4	0.7
IRA -> E1	0.8
IRA -> E2	0.7
IRA -> E3	0.8
FD -> F5	0.7
FD -> F6	0.7
FD -> F7	0.7

The results from **Model 2** (Table 5) which was the final model, are presented in the subsequent sections of this paper. The first column of Table contains the original parameters obtained by applying the *samples* function. 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. For significance testing of path estimates (loadings and path coefficients), the researchers used 500 bootstrap samples, and used ones to initialize the outer weights. The researchers obtained the bootstrap confidence intervals using the method of generating confidence intervals by [37], which leads to more accurate coverage rates in the event that the distribution of bootstrap draws is not normal.

Table 5. Bootstrap Estimates, Standard errors, and 95% Confidence Intervals for the Path Estimates [Path-A, Estimate-1, Mean Bootstrap Estimate-2, Bias-3, Standard Error-4, 95% bca Confidence Interval-5]. Outer Model: Lower-B, Upper-C; FC-D, IRA-G, & FD-H

A			1	2	3	4	5	
Outer Model								
							B	**C**
D	>	C1	0.88	0.88	-	0.03	0.80	0.9
D	>	C2	0.87	0.87	-	0.04	0.76	0.9
G	>	E1	0.81	0.80	-0.01	0.07	0.61	0.9
G	>	E2	0.76	0.75	-0.01	0.09	0.52	0.9
G	>	E3	0.77	0.77	-0.01	0.08	0.56	0.9
H	>	F5	0.75	0.74		0.06	0.60	0.8
H	>	F6	0.80	0.79	-0.01	0.05	0.69	0.9
H	>	F7	0.71	0.70	-0.01	0.07	0.55	0.8
Inner model								
D	>	G	0.30	0.32	0.01	0.08	0.08	0.4
D	>	H	0.32	0.33	0.01	0.08	0.16	0.4
G	>	H	0.2	0.2	0.01	0.1	-0.09	0.3

*Significant at α=0.05.

Table 5 also shows the regression results of financial distress (FD) on fraudulent claims (FC), and IRA supervision. The structural path from FC to FD was found to be significant at 5% level of significance. Financial Distress (FD) increased with increased risk of fraudulent claims (FC) giving a regression coefficient, β= 0.32, at 95% CI= (0.16, 0.4). This relationship was significant. In other words, for every unit increase in FC, FD significantly increased by 0. 32.

4.8. Effects

Table 6 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 [31]. The direct effects are usually given by the path coefficients, as can be seen in the 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 6, FC affect FD both directly, and indirectly through IRA supervision. The indirect effect of FC on FD via IRA is 0.0452.

Table 6. Total, Direct and Indirect Effects

Paths	Direct	Indirect	Total
FC -> IRA (b)	0.30225	_	0.30225
FC -> FD (b via c)	0.31777	0.0452	0.36297
IRA -> FD (c)	0.14966	_	0.14966

4.9. 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 the researchers investigated whether the indirect effect $b \times c$ was significant at 5% level of significance.

Table 7. Summary of Mediating effects Tests

	Coefficient	Bootstrap 95% CI (Bias-corrected)	
Direct effects		**Lower**	**Upper**
B	0.30225	0.1651	0.4563
C	0.14966	-0.0260	0.3242
Indirect effects			
$b \times c$	0.0452	-0.0105	0.1034

From Table 7, the indirect effect $b \times c$ was not significant at 5% significance level. Hence, hypothesis Ho3 is supported. The researchers 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 fraudulent claims (FC) and financial distress (FD). However, the direct effects of FC on FD (path **a**) and IRA (path **b**) proved significant. This means that hypotheses Ho1 and Ho2 are not supported. That is, there is a significant relationship between FC and FD; and there is also a relationship between FC and IRA supervision.

4.10. Model Evaluation of the Measurement Model

The fit measures suggested a good model fit as shown by the actual values against the preferred values (Table 8). The results of the PLS-SEM model, using structural model path weighting scheme, show a moderate R-square value of 0.15 for Financial Distress, and a weak level of 0.091 for IRA supervision (Table 10).

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. All the values of Dillon-Goldstein's ρ values lead to acceptance of unidimensionality of all blocks, thus supporting homogeneity of the indicators.

Table 8. Dimensionality Indices

Block	Number of MVs	Dillon-Goldstein's ρ	Preferred value	Conclusion
FC	2	0.86	>0.7	Good fit
IRA	3	0.83	>0.7	Good fit
FD	3	0.80	>0.7	Good fit

4.11. Discriminant Validity of the Measurement Model

The quality of the measurement model was also examined by checking discriminant validity of the loadings and path coefficients [30]. 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 associated with a given LV should be greater than their loading with any other LV. In Table 9, 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 0.2, at which cross loadings were to be printed. All the MVs, therefore, agree with their own LVs, supporting discriminant validity of the LVs.

Table 9. Loadings/ Correlations between MVs and LVs

	IRC	IRA	FD
C1	0.8753		
C2	0.8690		
E1		0.8092	
E2		0.7635	
E3		0.7747	
F5			0.7479
F6			0.8004
F7			0.7062

4.12. Model Evaluation of the Structural Model

Structural model path coefficients

As Table 10 shows, effect of fraudulent claims (FC) on both financial distress (FD) and IRA supervision were statistically significant at 5% significance level (95%CI: (0.155, 0.441) and (0.078, 0.418), respectively). The *pathDiagram()* function returns the graphical representation of the hypothesized / postulated model with loadings and path coefficients. The loadings and path coefficients in Table 10 can easily be viewed in Figure 4. To check the statistical significance of the regression coefficients, Table 6 should be referred to.

Communality and Redundancy

The communality indices in Table 10 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 [36]. Coefficients of determination (R^2 values) indicate the quantity of the variance in the endogenous LVs explained by their exogenous LVs.

Table 10. Coefficients of determination, R^2, Communality and Redundancy

Block	Number of MVs	R^2	Communality	Redundancy
FC	2		0.76	
IRA	3	0.091	0.61	0.056
FD	3	0.152	0.57	0.086
Average		**0.12**	**0.63**	**0.071**

The coefficient of determination of 15.2% for financial distress (FD) indicates a moderate level of model fitness. The value means that 15.2% 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 above 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 0.28 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.

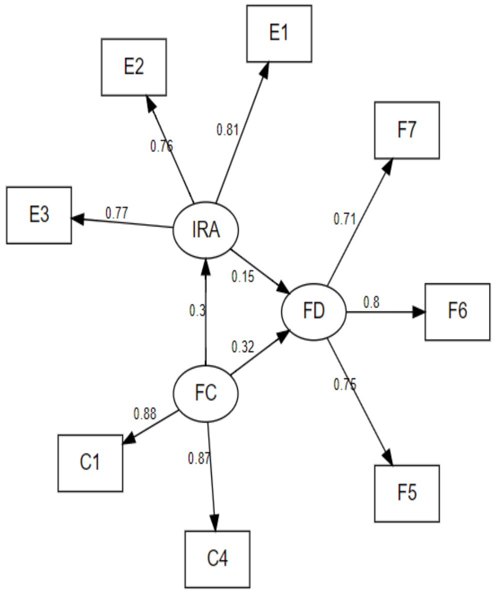

Figure 3. A path diagram for the fitted PLS-SEM model

4.13. Hypothesis Testing

As per the initial hypothesized model: 'there is no significant effect of fraudulent claims on financial distress in non- life insurance companies in Kenya (Ho1)'; 'there is no significant relationship between fraudulent claims and IRA supervision (Ho2)'; and 'there is no significant mediating effect of IRA's supervision on financial distress (Ho3)'.

After the results from PLS-SEM, the confidence intervals for the factor loadings indicate that there is an effect of fraudulent claims on financial distress in non- life insurance companies in Kenya (i.e., fraudulent claims positively influence financial distress); there is a relationship between fraudulent claims and IRA supervision, and IRA's supervision role is not a mediating factor of financial distress.

Finally, the hypotheses results are as follows:

Ho1: Reject
Ho2: Reject
Ho3: Accept

5. Conclusion and Discussions

In this study we set out to investigate the impact of fraudulent 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 fraudulent claims (FC) 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 fraudulent claims lead to financial distress in non-life insurance companies in Kenya. The structural path from FC to FD was found to be significant at 5% level of significance. Financial distress (FD) increased with fraudulent claims (FC) with a regression coefficient of β= 0.32, (95% CI= (0.16, 0.4)). In other words, for every unit increase in FC, FD significantly increased by 0.32. The respondents (26.5%) confirmed from the survey that insurance companies were under reserving claims thus reporting higher profits, giving rise to higher perks to employees and dividend payments shareholders. This gave rise to heavy cash outflow constraining cash available to pay claims and other creditors.

However, there were limitations of this study. The postulated model did not incorporate other factors that may affect financial distress in non-life insurance companies; only one exogenous variable, fraudulent claims, 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. 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, and not specifically for non-life insurance companies.

Future studies could address some of these study's limitations. First, more exogenous variables should be included in the studies; effects of corporate governance, financial management, 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 in 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 non-life insurance companies, rather than using the Altman's model. Alongside these limitations, this study had several advantages and strengths; the findings are important contributions to understanding that fraudulent claims in non-life insurance industry in Kenya is real, and 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 PLS-SEM. PLS-SEM allowed researchers to test multiple relationships simultaneously (mediating effects) within a postulated conceptual model using one variable. This is important in research where several mediating variables are suspected to have complex inter correlations.

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