Modelling the Effect of Pure Risk and Risk Due to Catastrophic Events on Microinsurance Claims:

Empirical Evidence from a Microinsurance Company in Ghana

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Abstract

Microinsurance Companies face two daunting issues when it comes to pricing of their products. First is the small ticket size of microinsurance premiums and secondly, lack of data as well as inadequate proper storage of records. These do not allow for proper pricing of products which could lead to inefficient reserving and render claim books vulnerable to catastrophes. This research considered whether such catastrophes known as “Act of God” risks, do have an effect on the claims book. The study made use of some sampled continuous probability distributions to model the microinsurance claim sizes which comprised Manmade as well as Act of God risk claims. The research further looked at, amongst the sampled distributions, which one best models claim size by carrying out a number of best fit tests. The claim sizes data used suggest that they do not come from a normal population, therefore the Wilcoxon rank sum test was carried out to determine which one of the two types of claim sizes has a negative impact on the other. The final results showed
that the distribution that best models both claims data is the log-normal. The results further showed that an Act of God event can have a negative effect on the claims amount of a microinsurer or provider and this must be taken into account when pricing such products.

**Keywords:** Mortality Rate, Interest Rate, Expense Factor, Probability Distribution, Manmade Claim, Act of God Claim, Ghana

1 Introduction

Low income households are mostly exposed to a number of high risks that make them vulnerable to an insurance take-up program, reduce their ability to enroll on any insurance or hinder their economic welfare. These risks range from illness, unemployment to lack of proper education among others. Quite a number of researches (Churchill, Reinhard & Qureshi [7], Churchill [6], Makove [12], Owuor [15] among others) have shown that these risks have important implications for the low-income earner and to society in general leading to calls to establish safety nets to protect these households. Microinsurance is one such safety net provided within the insurance industry to protect the low-income earner. It is the provision of insurance policies designed purposely to meet the needs of low-income people. It is basically the same as regular insurance but the difference is that it targets low-income groups. These defining features are reinforced by the International Labour Organization’s (ILO) point of view, that microinsurance can be seen from two complementary perspectives, namely, (1) a way of extending social protection to excluded population and (2) a new market for the insurance industry.

Aseffa [4], citing CGAP Working Group (2003) and IAIS Issues Paper (2007) respectively, provides more specific definitions of microinsurance as “the protection of low-income people against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved” and as “the provision of cover to a specific market segment, thus low-income persons”. However, due to the varying definitions or classifications of the low-income people from country to country, the threshold for a person to be entitled to a microinsurance product will also vary. What, nonetheless, remains the same is the target group, that is, the low-income earner.

The risks microinsurance clientele face are measured per their severity or frequency. These risks affect the pricing of premiums which in turn affects the microinsurance portfolio. Pricing is usually done by calculating the expected claims,
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administrative cost, risk premium and profit margin of a product before it is released into the market (Association of Kenya Insurers, [2]).

For this study, risks are categorized into two forms; namely, Pure Risk and Act of God risk. Pure risk is, the situation that holds out on the possibility of loss e.g. Incapacitation, Death, Hospitalization etc. on the part of the insured. Risks due to “Act of God” are events that occur through natural causes and cannot be avoided through the use of caution and preventative measures. In essence, the phrase “Act of God” refers to natural disasters that have catastrophic effects. For example, storms, hurricanes and tornadoes.

The data set used in this research consists of claim amount, type of risk and dates of reported claims. The objective of this research was to ascertain whether or not one of the two categorized risks has an effect on the claims amount paid out, its severity and if data are normally distributed for both types of risks.

This work is divided into five sections. In the next section, an explanation of the methodology and the dataset is offered. The third section presents the analysis of the results and in section four and five, we present our concluding remarks, highlight the major contribution of the study and make recommendations for further research.

1.1 Problem Definition

Low-income households are vulnerable to risks and economic shocks. A way forward for the poor to protect themselves is through insurance. In order to help low-income households to manage their risks, micro insurance assists them in maintaining a sense of financial confidence even in the face of significant vulnerability (Churchill & Matul [8]). Additionally, poor women are most likely vulnerable to risks related to health, income generation, old age and death. (Banthia, et al. [5]).

A risk is defined as an uncertain event and is an adverse risk when it has negative impact. In order to quantify the expected size of claim amount under microinsurance, the exact distribution of the claim amount needs to be determined in an efficient manner so as to quantify the needed premium appropriately.

This paper therefore defines these risks by classifying them into two different forms, as indicated earlier, determining their respective distributions and estimating their impact on the total claim amount of the microinsurance entity.
1.2 Research Objectives

The general objective of this research was to determine the various risks that affect the poor and low-income groups in Ghana. Specifically, the research sought to evaluate the effects of manmade risks and risks due to “Act of God” on microinsurance claims.

2 Materials and Methods

In order to qualitatively describe the risks, we have grouped them as mentioned earlier into two main categories, namely, Pure Risk– risks that occur naturally and Act of God– risks that occur due to Acts of God. Microinsurance policies are designed to be simple and easy to understand. The risks covered are very specifically stated to avoid any ambiguity during claims payment.

Hence, microinsurers are very much aware of the risks to which they have contracted their clients. However, sometimes, due to the many social risks faced by this clientele’s base, some risks occur that fall within the Act of God disasters that are totally unpredicted and leave the books of the microinsurer totally exposed. This puts the microinsurer in a very compromised state.

The risk classification is very important during pricing and reserving. The pure risk has a direct influence on the pricing and reserving of the company. With these risks, the company can eliminate or reduce the exposed risk. Even in some of these cases the book of the microinsurer is totally left exposed although it could have been easily avoided.

The pricing of premiums of an insurance company is based on the following factors; the mortality rate or the rate of occurrence of an event, prevailing interest rate and the expense factor of the company. These factors are briefly explained below.

**The mortality rate:** Mortality rate is the number of death per 1,000 per year over a certain population. This rate can be affected by social factors like health care and maternal death.

**Rate of occurrence of event:** How often an event occurs in a particular area or within a population will determine the rate of occurrence. The rate of occurrence can either be frequent and hence effect will be minimized and over a long period or can be severe and has a one-off occurrence.
**Interest rate:** Companies invest their premiums and assume they will earn a certain level of interest rate. Most microinsurers operate in developing countries where interest rates are high, so this is very instrumental in their pricing.

**Expense factor:** This area can vary from company to company since each company’s expense might differ. The expenses are spread over the premiums and this is known as the expense loadings.

The microinsurer clientele faces a certain level of risks that does not make it practicable in rating their premium in the same fashion as those for the traditional insurer. Rating in the same traditional way as done for the conventional insurer might lead to a lot of these companies folding up. However, the lack of data in microinsurance has led most microinsurers to still rate premium as they do with traditional insurance pricing. This research therefore addresses whether there is an impact of the Act of God on the claims payment of a microinsurance company. The effect, whether it is positively or negatively related to the total claim book was assessed.

The data used for the analysis were the total claim amounts of a microinsurer available. The total claims data covering 2013 to 2016 of a microinsurance provider in Ghana were collated and data divided into the two categories of risks described below;

1. Claims data that covers clientele who claimed under pure risk events, that is, priced using the pricing formula explained above.

2. Claims data that covers clientele who claimed under the Act of God events. With this, the insurer has no pricing formula.

The researcher used modeling process to establish among the sampled distributions, which one will effectively model the claims and in addition conduct goodness of fit test using the Akaike’s Information Criterion (AIC) and graphically using the Quantile-Quantile (Q-Q) plots. The various risks were isolated and analysed to verify which of these risks impact heavily on the data. This was to help us model and predict which of the risks influence the claims portfolio of the Microinsurance Company. The R Software was used to run the various tests.

**2.1 Selection of Probability Distributions for Modeling.**

Distribution for claims presents the pattern in which claims are borne by an insurer in a specified period of time. The distribution can be in terms of either claims...
frequency or claims sizes (amount). When the claim frequencies and the claim sizes are to be considered together, an aggregate claims distribution is obtained. Theoretical distributions such as the Poisson and Binomial distributions are usually used to model the number of claims since it involves a discrete random variable, that is, count data. Whereas continuous distributions such as Gamma, Pareto, Normal, Log-normal and others are used to model the distribution of claim size since it is a continuous random variable. Exponential, Normal, Pareto, Gamma, Weibull and Burr distributions are the common statistical distributions used to model claim sizes. This is because, these distributions have positive skewness and as a result, they become very useful in modeling claim sizes since an insurer generally experiences a large number of small claims compared to large claims which indicates positive skewness (Mazviona & Chideiza, [13]).

This research aims at modeling the microinsurance claim sizes (amount) and therefore makes use of Exponential, Log-normal and Weibull distributions for the modeling process. These models are informative to the company and enable decision making, amongst other things on premium loading, expected profits, reserves necessary to ensure (with high probability) profitability and the impact of reinsurance and deductibles.

2.2 Description of Data for the Analysis

Empirical data were collected from a microinsurance company in Ghana. The data spanned from 2014 to 2016 and contained the individual date of each claim payment, type of risk claimed on and the claim amount for each individual claim.

The data were subdivided into two categorized risk forms and the data were analysed to find the various salient features of the respective distributions. These helped in the selection of the distributions to be considered for the analysis.

2.3 Maximum Likelihood Estimators

The maximum likelihood is intuitively appealing and this is because an attempt is made to find the values of the true parameters that would have most likely produced the data that are in fact being observed. Also, practically the performance of maximum likelihood estimators is optimal for large enough data (Ramachandran and Tsokos, [16])

In addition, maximum likelihood is considered as a method of estimation and inference for parametric models. The maximum likelihood estimator is the value of
parameter (or vector of parameters) that makes the observed data most likely to have occurred given the data generating process assumed to have produced the variable of interest (Denuit et.al [9]).

The method of maximum likelihood estimation was applied for the estimation of the parameters. This is because maximum likelihood estimators are very useful in the sense that they have some important properties which include consistency, asymptotic normality and invariance.

2.4 Probability Distributions Considered

According to Olive (2010), the likelihood and log-likelihood functions of the sampled distributions are given as follows:

2.4.1 Log-Normal Distribution LN($\mu$, $\sigma^2$)

If $Y$ has a lognormal distribution, denoted $Y \sim LN (\mu, \sigma^2)$, then the probability density function of $Y$ is given by

$$f(y) = \frac{1}{y\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{[\log(y) - \mu]^2}{2\sigma^2}\right\}$$

where $y > 0$ and $\sigma > 0$ and $\mu$ is real.

Hence the likelihood function, $L(\mu, \sigma^2)$ is given by

$$L(\mu, \sigma^2) = \prod_{i=1}^{n} \frac{1}{y_i\sqrt{2\pi\sigma^2}} \exp\left(-\frac{[\log(y_i) - \mu]^2}{2\sigma^2}\right)$$

(2)

If $Y_1, \ldots, Y_n$ are independent and identically distributed LN($\mu, \sigma^2$) where $\mu$ is known, then the likelihood function given in (2) then becomes

$$L(\sigma^2) = c \frac{1}{\sigma^n} \exp \left[-\frac{1}{2\sigma^2} \sum_{i=1}^{n} (\log(y_i) - \mu)^2\right].$$

(3)

and its corresponding log likelihood is

$$\log L(\sigma^2) = d - \frac{n}{2} \log(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{n} (\log(y_i) - \mu)^2,$$

(4)

Hence,

$$\frac{d}{d\sigma^2} \log L(\sigma^2) = -\frac{n}{2\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum_{i=1}^{n} (\log(y_i) - \mu)^2.$$  

(5)

Setting $\frac{d}{d\sigma^2} \log L(\sigma^2) = 0$, 

...
we have;

\[
\sum_{i=1}^{n} (\log(y_i) - \mu)^2 = n \sigma^2 \quad \text{or}
\]

\[
\hat{\sigma}^2 = \frac{\sum_{i=1}^{n} [\log(y_i) - \mu]^2}{n}
\]

If \(Y_1, \ldots, Y_n\) are independent and identically distributed LN(\(\mu, \sigma^2\)) where \(\sigma^2\) is known, then the likelihood function is given by

\[
L(\mu) = c \exp \left(\frac{-n \mu^2}{2\sigma^2}\right) \exp \left(\frac{-n}{\sigma^2} \sum_{i=1}^{n} \log(y_i)\right)
\]

and the corresponding log likelihood is

\[
\log L(\mu) = d - \frac{n \mu^2}{2\sigma^2} + \frac{\mu}{\sigma^2} \sum_{i=1}^{n} \log(y_i)
\]

Hence,

\[
\frac{\partial}{\partial \mu} \log L(\mu) = -\frac{2n \mu}{2\sigma^2} + \frac{\mu}{\sigma^2} \sum_{i=1}^{n} \log(y_i)
\]

Setting \(\frac{d}{d\mu} \log L(\mu) = 0\), we get;

\[
\sum_{i=1}^{n} \log(y_i) = n \mu \quad \text{or}
\]

\[
\hat{\mu} = \frac{\sum_{i=1}^{n} \log(y_i)}{n}
\]

### 2.4.2 Weibull Distribution \(W(\beta, \eta)\)

If \(Y\) has a Weibull distribution, denoted as \(X \sim W(\beta, \eta)\), then the probability density function of \(Y\) is given as:

\[
f(x) = \left(\frac{\beta}{\eta}\right) \left(\frac{x_i}{\eta}\right)^{\beta-1} \exp\left(-\frac{x_i}{\eta}\right)\beta
\]

The likelihood function is \(L(x_1, \ldots, x_n, \beta, \eta)\), which is equal to

\[
L(x_1, \ldots, x_n, \beta, \eta) = \prod_{i=1}^{n} \left(\frac{\beta}{\eta}\right) \left(\frac{x_i}{\eta}\right)^{\beta-1} \exp\left(-\frac{x_i}{\eta}\right)\beta
\]
On taking the logarithms of equation (11), differentiating partially with respect to \( \beta \) and \( \eta \) in turn and equating to zero, we obtain the estimating equations as

\[
\frac{\partial}{\partial \beta} \log L (\beta) = \frac{n}{\beta} + \sum_{i=1}^{n} \ln x_i - \frac{1}{\eta} \sum_{i=1}^{n} x_i^\beta \ln x_i
\]

(12)

\[
\frac{\partial}{\partial \eta} \log L (\eta) = -\frac{n}{\eta} + \frac{1}{\eta^2} \sum_{i=1}^{n} \ln x_i
\]

(13)

Al-Fawzan [3], indicated that on eliminating \( \eta \) between equations (12) and (13) and simplifying, we have:

\[
\frac{\sum_{i=1}^{n} x_i^\beta \ln x_i}{\sum_{i=1}^{n} x_i^\beta} = -\frac{1}{\beta} - \frac{1}{n} \sum_{i=1}^{n} \ln x_i
\]

(14)

which may be solved to get the estimate of

\[
\hat{\mu}_k = \hat{\beta}
\]

(15)

This can be accomplished by the use of standard iterative procedures (i.e. using Newton-Raphson’s method). Once \( \beta \) is determined, \( \eta \) can be estimated using equation (14) as

\[
\hat{\eta} = \frac{\sum_{i=1}^{n} x_i^\beta}{n}
\]

(16)

### 2.4.3 Exponential Distribution

If Y has an exponential distribution, \( Y \sim \text{Exp} (\lambda) \), then the probability density function of \( Y \) is

\[
f(y) = \frac{1}{\lambda} \exp \left( -\frac{y}{\lambda} \right) I_{(y \geq 0)} \quad \text{where} \quad \lambda > 0,
\]

(17)

The likelihood function which is given by \( L (\lambda) \) is equal to

\[
L (\lambda) = \prod_{i=1}^{n} \frac{1}{\lambda} \exp \left( -\frac{y_i}{\lambda} \right) = \frac{1}{\lambda^n} \exp \left[ -\frac{1}{\lambda} \sum_{i=1}^{n} y_i \right]
\]

(18)

and the log likelihood is

\[
\log (L (\lambda)) = -n \log (\lambda) - \frac{1}{\lambda} \sum_{i=1}^{n} y_i
\]

(19)
Hence,
\[
\frac{d}{d\lambda} \log L (\lambda) = -\frac{n}{\lambda} + \frac{1}{\lambda^2} \sum_{i=1}^{n} y_i
\]  
(20)

Setting \( \frac{d}{d\lambda} \log L (\lambda) = 0 \),

we obtain;
\[
-\frac{n}{\lambda} + \frac{1}{\lambda^2} \sum_{i=1}^{n} y_i = 0
\]

which yields;
\[
\sum_{i=1}^{n} y_i = n\lambda \quad \text{or} \quad \hat{\lambda} = \bar{y}
\]  
(21)

2.4.4 Goodness of Fit Tests

The goodness of fit test to establish the quality of data was employed using the Akaike’s Information Criterion (AIC) and graphically using the Quantile-Quantile (Q-Q) plots to test the quality of data to be used.

The Akaike’s Information Criterion (AIC) is defined by:
\[
\text{AIC} = -2(\text{maximized log-likelihood}) + 2(\text{number of parameters estimated}).
\]

When two models are being compared by using Akaike’s Information Criterion (AIC), the model with the smaller AIC value is the more desirable one (Achieng, [1]).

The criterion for the selection of the appropriate distribution was based on the following hypotheses:

\( H_0 \): All the sampled distributions provide similar fits of a statistical model for the claims data
\( H_1 \): At least one of the sampled distributions provides the best fit of a statistical model for the claims data

3 Data Analysis and Results

Here, we present the analysis and results of the data used in the study.
Table 1 presents the summary statistics of the two types of claims data. Here, the data sets are heavily skewed positively with skewness coefficients of 13.15 and 13.41 respectively for the manmade risk as well as the Act of God events. As indicated by the histograms in Figures 1 and 2, it is obvious that indeed the claims data have heavy right-tailed as well as being leptokurtic distribution. This indicates that most of the claim amounts are very low in value. Additionally, the Act of God had a larger mean value (Ghs$^{1}$ 2,177) than that of the Manmade claim value of (Ghs 1,186). Also, the variability in the claim amounts is larger with respect to the Act of God claims than that of the Manmade.

### Table 1: Descriptive Summary Statistics of the Types of Claims

<table>
<thead>
<tr>
<th>Type of Claim</th>
<th>Sample Size</th>
<th>Mean</th>
<th>Median</th>
<th>St. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manmade (Natural Causes)</td>
<td>1872</td>
<td>1186</td>
<td>500</td>
<td>2543.26</td>
<td>13.15</td>
<td>239.07</td>
</tr>
<tr>
<td>Act of God Causes</td>
<td>684</td>
<td>2177</td>
<td>1478</td>
<td>3538.19</td>
<td>13.41</td>
<td>257.37</td>
</tr>
</tbody>
</table>

Source: Researcher’s computation

1. Ghs is the Ghana Cedi official abbreviation

![Figure 1: Histogram of the Act of God claims amount](image)
To reduce the skewness of the claims data, log transformation was used. The log transformations of the data were obtained using the R statistical software. The histogram of the log-transformed data is shown in Figures 3 and 4, which now depict normal curves with less skewness.
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Figure 4: Histogram of the log transformation of Pure Risks claims amount

The log of the claim data due to its low skewness as shown above in Figures 3 and 4 is used to compute the maximum likelihood estimates of the sampled distributions. Fitting the model to a claim data is the first step in finding the parameter estimates of the three chosen statistical distributions.

It is well known that the maximum likelihood estimators of the two parameters in the Gamma distribution does not have closed form solution which causes difficulties in some applications (Ye & Chen, [17]). It must also be noted that although the Gamma distribution is appropriate for heavy tailed data, particularly for modeling insurance claims, in our case, the distribution could not be used because there were some difficulties associated with the maximum likelihood estimators of the distribution. This is because, after running the analysis, there was a very large positive skew for both claims as shown in Table 1.

Koutrouvelis and Canavos [11] used Empirical Moment Generating Function for estimating the shape, scale and location parameters of the three-parameter gamma distribution so as to avoid the difficulties associated with maximum likelihood estimation when the sample has a very large positive skewness.

The AIC was used to select the most appropriate distribution. Thus, the distributions chosen were therefore Weibull, Lognormal and exponential functions (See Table 2).
Table 2: Summary of the Estimation Results of the Various Types of Claims

<table>
<thead>
<tr>
<th>Type of Claim</th>
<th>Distribution</th>
<th>Log-Likelihood</th>
<th>AIC</th>
<th>Parameters</th>
<th>BIC</th>
<th>P-Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Man made</td>
<td>Weibull</td>
<td>-15103.85</td>
<td>30211.7</td>
<td>$\mu$=0.9163132, $\Phi=1120.90314$</td>
<td>30222.77</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td></td>
<td>Lognormal</td>
<td>-14790.43</td>
<td>29584.87</td>
<td>$\mu=6.5349588$, $\Phi=0.9483569$</td>
<td>29595.94</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>-15122.42</td>
<td>30246.85</td>
<td>$\mu=0.000843275$</td>
<td>30252.38</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>God made</td>
<td>Weibull</td>
<td>-5939.659</td>
<td>11883.32</td>
<td>$\mu=1.043772$, $\Phi=2224.543404$</td>
<td>11892.37</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td></td>
<td>Lognormal</td>
<td>-5846.102</td>
<td>11696.2</td>
<td>$\mu=7.2696459$, $\Phi=0.8679235$</td>
<td>11705.26</td>
<td>0.031689</td>
</tr>
<tr>
<td></td>
<td>Exponential</td>
<td>-5941.1</td>
<td>11884.2</td>
<td>$\mu=0.0004559295$</td>
<td>11888.73</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

Source: Researcher’s computation

Table 2 shows that the Log-normal distribution best fits both datasets. This is because among the sampled distributions used to model the claims, the log-normal had the largest log-likelihood values of -14790.43 and -5846.102 for both Manmade and Act of God claims respectively. Besides, considering the AIC values, the log-normal had the smallest values of 29584.87 and 11696.2 respectively for manmade and Act of God claims. The data were also tested for normality and all indications showed that the data were not normally distributed.

![Q-Q plot](image-url)  

Figure 5: Q – Q Plot of Pure Risk Claims data
Figures 5 and 6 show the Q-Q plots for all the three distributions for both claim amounts (the pure risk and the Act of God events). The log-normal distribution values are closer to the reference line which is an indication of a good fit. The points of the other distributions look more spaced out. This shows and confirms that the log-normal distribution better fits the data.

3.1 Test for fitted models

There was also the need to conduct a test to find out which of the claims has a negative impact on the other. The following hypotheses were used:
H₀: The mean of the Man-made risk claim amount is equal to the mean of the Act of God risk claim amount.
H₁: There is a difference in the mean of Man-made risk claim amount and Act of God risk claim amount.

To compare two groups of continuous data which are not normally distributed, the Wilcoxon test is recommended. The data used for the analysis as indicated in the Q-Q plots and the histogram plots are not normally distributed and therefore the Wilcoxon rank sum test (W) which is described as the non-parametric version of the two-sample t-test was used for the test.
The calculated Wilcoxon rank sum test gave values of $W = 348,810$ and a p-value of ($< 0.001$).
Since the p-value was found to be less than $0.001$ ($< 0.001$), this indicates that the mean value of Act of God event claim amount has a larger mean than that of the Pure risk and as a result, Act of God event claims have greater impact on claim size than that of pure risk claims. Hence the null hypothesis was rejected.
This also shows that an Act of God event can have a negative effect on the claims amount of a microinsurer provider and this must be taken into account when pricing such products.

4. Discussion of Results

Our results of fitting the distributions for both types of claims, that is, the manmade and Act of God risks, the log-normal distribution fitted well which is heavily skewed positively and was consistent in principle to Eling’s [10] and Mazviona and Chideiza’s [13] findings. They fitted distributions to insurance claim data and found out that the skewed-normal and the skewed-student models were optimal. This is so because the log-normal distribution falls in the class category of positively skewed-normal distribution. The negative effect of Act of God claims on total claim size than that of manmade claims. Arguably, even though Act of God events are natural and happen occasionally, when they do, they are catastrophic and cause losses at higher magnitudes making the average claim size of events due to Act of God being double that of manmade.

5. Conclusion and Recommendation

In conclusion, the two types of claims, that is, Manmade and Act of God events have similar distributions. Both being heavily skewed to the right and leptokurtic in nature. However, the Act of God event is more peaked than that of the Manmade event. The log-normal distribution fitted both data sets optimally. Furthermore, Act of God events rarely occur but when they do, the claim amount averages more than twice that of the Manmade events. It was also observed that Act of God events have a negative effect on the books of the microinsurer more than Manmade events.

We thus recommend that in setting up premiums the weighting must reflect the respective distributions so as not to throw the books of the microinsurer into disarray.
We recommend a further study to produce a formula for the microinsurance industry that will enable us develop a tool that has additional ratings to cater for the effect of Act of God events on the portfolio of a microinsurance company.

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