ASSESSING THE PROFITABILITY OF MICROHEALTH INSURANCE IN KENYA

SAC 420 – Project in Actuarial Science

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School of Mathematics

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Bachelor of Science in Actuarial Science

Declaration

We hereby declare that this project is our original work and has not been presented before in any other academic institution for any academic award.

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On this .... day of .... 2025.

Dedication

This project is dedicated to our families, for their constant love, support and encouragement that has made this journey possible.

Acknowledgement

We are deeply grateful to our supervisors, Prof. Mwaniki and Prof. Ogutu, for their invaluable guidance and support throughout this project.

Finally, we thank the Almighty for providing us with the strength and endurance to complete this journey.

Abstract

This study examines the long term profitability and financial sustainability of microhealth insurance (MHI) schemes in Kenya using actuarial and analytic methods. Rated as a developing country,Kenya's journey towards Universal Health Coverage (UHC) opens doors for MHI schemes to of fer products to the low income populations. However, despite the potential for expansion, they face significant challenges such as operational inefficiencies, high claim volatility and regulatory constraints.

Through sensitivity and scenario analyses, this research evaluates the impact of varying coverage limits, premium structures, policy numbers and administrative expenses on profitability. Insights detailed herein emphasize the role of optimized affordable premium structures with respect to great benefits paid out and the importance of robust risk management in scaling MHI schemes. It broadly supplements the country's discourse on achieving UHC and similar low-resource settings.

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List of Abbreviations

MHI	Micro Health Insurance
NHIF	National Hospital Insurance Fund
SDG	Sustainable Development Goal
UHC	Universal Health Coverage
LMIHs	Low and Middle-Income Households
FSD	Financial Sector Deepening
IRA	Insurance Regulatory Authority
NGO	Non-Governmental Organization
CBHI	Community-Based Health Insurance
OOP	Out Of Pocket
OOPE	Out Of Pocket Expenditure
ILO	International Labour Organisation
KHHEUS	Kenya Household Health Expenditure and Utilisation Survey
KeNADA	Kenya National Data Archive
EA	Enumeration Area
CRM	Collective Risk Model
AIC	Akaike Information Criterion
MLE	Maximum Likelihood Estimation
KDE	Kernel Density Estimation
SSP	Sampoorna Suraksha Programme
CHE	Catastrophic Health Expenditure

1 INTRODUCTION

1.1 Background Of The Study

Microhealth insurance schemes are designed to meet the health needs of the underserved by pooling risks and resources at the community level. They offer simplified enrollment processes and affordable premiums, making them accessible to informal sector workers and rural populations. These schemes have gained traction in various regions of Kenya, supported by non-governmental organizations and government initiatives such as the National Hospital Insurance Fund (NHIF) Supa Cover program.

Notably, the promotion of microhealth insurance aligns with Sustainable Development Goal (SDG) 3, which aims to ensure healthy lives and promote well-being for all at all ages. Specifically, SDG 3.8 emphasizes achieving universal health coverage (UHC), including financial risk protection and access to essential health services. Microhealth insurance plays a critical role in advancing this goal by expanding coverage and reducing out-of-pocket healthcare spending among poor and vulnerable communities.

Access to affordable healthcare remains a pressing challenge in Kenya, particularly for low-income populations, who are typically defined as individuals or households living below the national poverty line. About 33.6% of Kenyans lived below the national poverty line as of 2019 (KNBS, 2020). These populations often face significant financial barriers when seeking medical care, making them highly vulnerable to health and economic shocks. Traditional health insurance schemes frequently exclude them due to high premiums, formal employment requirements, and limited coverage options. In response, microhealth insurance has emerged as a potential solution aimed at improving healthcare access through low-cost, community-based insurance models.

While the primary objective of microhealth insurance is to enhance healthcare access and financial protection, its long-term impact depends heavily on financial sustainability. This includes the ability of these schemes to consistently cover claims, manage administrative costs, and generate enough revenue to remain viable. Despite the growing interest in microhealth insurance in Kenya, there remains limited empirical research assessing its long-term profitability. Most existing studies focus on uptake and accessibility, with less attention paid to financial performance indicators such as claim ratios, premium adequacy, and reserve sustainability.

Assessing the long-term profitability of microhealth insurance schemes is essential not only to ensure the continuity of these services but also to support national health policy objectives and progress toward SDG 3. Insights from this analysis can guide policymakers, donors, and implementing agencies in designing financially sound microinsurance models that balance affordability with sustainability.

This study evaluates the financial sustainability and long-term profitability of microhealth insurance schemes in Kenya using actuarial and economic models and methods, with the aim of providing evidence-based recommendations for improving health financing systems.

1.2 Problem Statement

A substantial portion of the Low and Middle-Income Households (LMIHs) are individuals vulnerable to economic shocks, especially those triggered by health-related emergencies. The cost of medical care in Kenya remains high, forcing families to choose between their health and financial stability. For many, out-of-pocket hospital payments consume a disproportionate share of household income, pushing families deeper into poverty and perpetuating the cycle of economic insecurity. Additionally, the financial potential of the informal sector, which is a primary target for MHI, is generally low and inconsistent, posing challenges for sustainable premium payments (Okungu et al,. 2017).

MHI schemes emerged as a promising solution to address these issues by providing affordable, tailored health coverage to underserved populations. They are specifically designed for LMIH groups to bridge the healthcare gap and reduce the financial burden of the citizenry while ensuring top-notch medical services. Despite its potential, the long-term profitability of MHI schemes faced a variety of challenges which threaten their scalability and effectiveness. A 2024 report by Cenfri in conjunction with Britam and Swiss Capacity Building Facility, cites that less than 20% of Kenyans are enrolled in any form of health insurance, with MHIs being only a fraction of this coverage.

Several MHI schemes that targeted low-income households have been implemented in Kenya with varying degrees of success. Linda Jamii was a public-private partnership between Safaricom, Britam and Changamka micro insurance. The scheme was discontinued in September 2015 due to poor uptake and failure of the low-cost medical insurance model (Omondi, 2015). NHIF Supa Cover is a partially successful national scheme that extends benefits to the informal sector workers. The main issue is its financial sustainability as it has high premium costs for its users, slow processing and corruption claims. It shows promise for success but requires a more comprehensive actuarial assessment. Afya Yetu Initiative was a county-specific scheme, but it relied heavily on donor support. It struggled with inconsistent funding because the county governments lacked the financial capacity to sustain the programs.

Small risk pools limit the schemes' ability to generate adequate capitation funds to ensure consistent service delivery and claim coverage. Financial constraints are further exacerbated by operational inefficiencies, including high administrative costs, inadequate actuarial data for premium pricing and weak risk management practices. These factors collectively undermine the profitability and resilience of MHI programs in Kenya.FSD Africa reports that 71% of Kenyans cite lack of affordability as the reason for low health insurance uptake, followed by a lack of knowledge and awareness (about 20%).

The regulatory environment adds another complexity layer to the sustainability of MHIs. While the IRA and Health Ministry oversee aspects of health insurance, coordination between the health and financial sectors remains suboptimal. However, the regulatory framework for MHIs in Kenya is inadequate, lacking coordination between the health and financial sectors, which hampers strategic purchasing practices essential for sustainability(Munge et al., 2019).Policies governing MHI remain fragmented, lacking coherence to support innovation and scalability. An example is the absence of data sharing mechanisms between stakeholders, which limits the ability to monitor and evaluate the performance of these schemes.

This study evaluates the financial sustainability and long-term profitability of micro health insurance schemes in Kenya using actuarial methods and economic models, with the aim of providing evidence-based recommendations for improving health financing systems.

1.3 Objectives of Study

Primary Objective

To assess the long-term profitability of micro health insurance in Kenya using actuarial and analytical methods.

Secondary Objectives

1. To analyse loss ratios and evaluate the underwriting performance.
2. To apply sensitivity and scenario analysis to test the impact of varying claim frequencies, liability and premium structures on profitability.
3. To utilize risk models to determine claim distributions and estimate the profitability of the best-case scenario scheme.
4. Identify and recommend actuarially sound strategies to improve sustainability.

1.4 Significance of study

This study focuses on MHI as a critical solution to Kenya's healthcare challenges. It explores MHI's potential to address limited healthcare access, alleviate health-driven financial burdens and high out-of-pocket costs that deepen poverty for low and middle-income households. By analysing the profitability of MHI, particularly in addressing challenges related to small risk pools and high claim ratios, the study aims to offer insights for enhancing affordable healthcare coverage. The study ultimately contributes to the delivery of equitable healthcare access in Kenya.

1.5 Limitation of Study

The key limitation we encountered during our study was the inability to access primary financial data from microhealth insurance schemes or insurance companies in kenya.Despite efforts to reach out, obtaining data was unsuccsessful because:

- Most insurers in kenya do not specifically offer dedicated MHI products, those that do were generally unwilling to share detailed financial information due to data confidentiality.
- Several MHI schemes identified during the preliminary phase of the study had been discontinued, making it impossible to gather complete and reliable historical data from them.

2 LITERATURE REVIEW

2.1 Microinsurance and Community-based Insurance

MHI is designed to offer financial protection against health-related risks and promote access to healthcare among the underserved. Policy contracts for health microinsurance usually have a one-year duration. The distinction between community-based insurance operations and microinsurance is on the basis of autonomy and scale (Dror and Jacquier, 1999). Community-based operations rely heavily on outside facilitators such as governments and NGOs, while microinsurance programs are independent enterprises. Additionally, microinsurance is not limited to single communities. In its conception, the operation is meant to connect and bring together numerous parties, excluded from insurance services through occupational and financial factors, for the purposes of risk pooling and coverage.

2.2 Case Study from India

According to Savitha and Kiran (2015), MHI schemes can play a crucial role in reducing poverty resulting from out-of-pocket healthcare expenses. Inadequate public health funding, limited social health insurance coverage, and low uptake of private insurance have intensified the vulnerability of low-income households. In response,MHI schemes have emerged as a potential solution to provide financial protection and improve access to healthcare services. This case study examines the Sampoorna Suraksha Programme (SSP), a microhealth insurance initiative implemented in Karnataka, India. A cross-sectional study was conducted involving 416 insured, 366 newly insured, and 364 uninsured households to evaluate the impact of SSP on key financial indicators.

Using linear and logistic regression analysis, the study assessed changes in out-of-pocket expenditure (OOPE), catastrophic health expenditure (CHE), non-medical consumption, hardship financing, and labour supply. The findings revealed that insured households under SSP experienced significantly lower OOPE, CHE, and reduced reliance on hardship financing. However, no significant effects were observed on overall consumption expenditure or labour supply outcomes.

This Indian case provides valuable insights for Kenya's healthcare financing landscape. Although the primary focus was on financial protection, the implications are relevant for understanding the sustainability and potential profitability of MHI schemes in similar socio-economic contexts. The reduction in health-related financial shocks among enrollees suggests that effective MHI schemes can not only protect households from impoverishment but also achieve financial viability through improved enrolment, lower claim ratios, and broader risk pooling. Lessons from SSP can thus inform the design and implementation of scalable, sustainable MHI models in Kenya.

2.3 The Kenyan Context

In Kenya, MHI gained attention as a potential tool for achieving UHC, particularly for informal sector workers and low-income earners who are often excluded from mainstream health insurance schemes like NHIF (Mathauer et al., 2019). Numerous programs, such as Linda Mama, NHIF Supa Cover for the informal sector, and several NGO-led initiatives, seek to reduce out-of-pocket (OOP) expenditures and promote health equity. Various NGOs, private insurers and community-based organisations have rolled out MHI schemes targeting rural and informal populations (Okech and Lelegwe, 2015). Consequently, a section of the target population has taken up insurance, with the employed and those in trade forming a larger percentage of those who enrol (Macharia et al., 2017).

Community-Based Health Insurance (CBHI) schemes have been widely studied for their potential in expanding healthcare access in low-income settings. Ekman(2004) explains that while CBHI programs may help reduce OOP spending and increase access to health care, they do not generate enough resources to cover medical costs. Furthermore, there is strong evidence that the programs still exclude the poorest in society. However, some successful CBHI programs exist under certain contexts and situations.

2.4 Implementation of MHI in Kenya

The success of any insurance product is dependent on various factors. MHI particularly thrives in an environment characterised by a large size of a pool of willing contributors (Fusheini et al., 2017). However, according to (Wrede et al., 2008), reaching the low-income markets requires designing products that are accessible in order to unlock demand in this sector.

One of the primary economic challenges facing micro health insurance in Kenya is the affordability of premiums. Studies have shown that a significant proportion of households, both insured and uninsured, find health insurance premiums unaffordable. For instance, in rural western Kenya, 60% of insured households and 80% of uninsured households reported that the monthly premium exceeded 5% of their total household expenditure, making it unaffordable(Maritim et al., 2023). This high cost barrier is particularly pronounced among low-income households, where healthcare spending already constitutes a significant portion of their budget.

The implementation of MHI faces a number of challenges that are mainly characteristic of the economic and literacy levels of the country. A study by (Chuma & Maina 2012) shows that while MHI improves access to healthcare, its sustainability is hampered by issues such as irregular premium payments, lack of health awareness and limited actuarial data for pricing and reserving

MHI in Kenya operates within a complex environment that limits its ability to deliver affordable and quality healthcare to the people who need it most. The sustainability of (MHI) in Kenya is challenged by inadequate regulatory frameworks, poor coordination between health and financial sectors, and limited benefits offered to low-income households(Munge et al,. 2019). MHIs often contract low-cost providers, which can compromise service quality. Without strategic purchasing practices and better integration into the broader health financing system, MHIs may struggle to contribute meaningfully to universal health coverage goals in Kenya.

Corporate effort and creativity are needed to establish markets in the population due to its dynamic nature. For micro insurance to be successful, it is necessary that providers understand the real needs of the low-income population (Mazambani and Mutambara, 2018). Good governance and management are also a necessity for micro insurers (McCord and Osinde, 2005).

2.5 Methods

Various measures to address these gaps have been proposed, including public-private partnerships (Patowala, 2017) and integration with digital health platforms (Cenfri, 2021). However, the long-term viability of MHI still requires robust actuarial and financial evaluations. Several frameworks, such as (Dror, 2001) and the ILO's Microinsurance Performance Indicators (Wipf et al., 2010), recommend quantitative metrics such as loss ratios and renewal rates as core sustainability indicators for microinsurance.

The loss ratio has been a foundational metric in traditional insurance and actuarial science, dating back to the early development of property and casualty insurance in the 19th century. Insurers used it to assess the adequacy of premiums relative to claims and to monitor financial performance over time. It gained popularity because it was simple and direct to interpret. The loss ratio, representing the portion of incurred claims to earned premiums, is still a critical indicator of an insurer's underwriting and financial performance and stability. In developing countries like kenya, loss ratios are critical for tracking the balance between financial inputs and healthcare outflows. An optimal loss ratio for MHI typically ranges from 60% to 80%(wipf et al.,2010), this signals that most of the premium is used for healthcare services while retaining a buffer for administrative costs.

Loss ratios have a significant effect on the general financial performance of a microinsurance company.(Ritho et al.,2023) found that higher loss ratios negatively impact the financial stability of insurance firms. He suggested that the effective management of claims and underwriting practices is essential for sustainability. Supporting this,(Wanjohi and Muthoni,2021) emphasized that reducing loss ratios is vital for enhancing the financial performance of insurance companies in Kenya.

Sensitivity analysis originated in operations research and systems modelling in the early to mid-20th century. It became widely used in finance, economics, and actuarial modelling to understand the robustness of predictions and outputs under uncertain conditions. It is employed to assess how variations in key assumptions, such as claim frequency, severity, and premium rates, affect insurance outcomes. It is integral in stress-testing financial models and evaluating the robustness of insurance portfolios under different scenarios.

For MHI schemes in Kenya, sensitivity analysis provides insights into how fluctuations in claim frequency, premium defaults, healthcare inflation, or member dropout affect financial viability. An application of sensitivity analysis to microinsurance schemes in Kenya and India demonstrated that small increases in healthcare utilisation or inflation could significantly erode financial reserves (Giné et al., 2012)

Risk models stem from probability theory and were formalised in insurance mathematics through the works of Filip Lundberg and Harald Cramér. These models quantify uncertainty and inform pricing, capital requirements, and solvency assessments. (Grigutis et al., 2023) explored ruin probabilities within renewal risk models, highlighting scenarios where insurers face guaranteed ruin under certain claim and premium conditions. (Vakili and Ghaffari-Hadigheh, 2023) introduced an uncertain programming approach to optimise reinsurance strategies, aiming to minimise the risk of ruin and enhance the financial resilience of insurance companies. In Kenya, the application of advanced risk models remains limited due to data constraints. However, their potential is significant. Some suggestions by the International Association of Insurance Supervisors call for incorporating risk-based capital models to help prepare for claim surges and economic shocks

Maximum Likelihood Estimation (MLE), first introduced by R. A Fisher in 1922 (Aldrich, 1997), is one of the most widely used methods for parameter estimation in statistical modelling. It operates on the principle of choosing parameter values that maximise the likelihood function, which quantifies how well the proposed model explains the observed data. In practice, however, the application of MLE requires assuming a specific distribution for the data, and it is sensitive to model misspecification. This limitation has led to the use of model selection criteria such as the Akaike Information Criterion (AIC) to compare different statistical models. Developed by Hirotugu Akaike (deLeeuw, 1992), the AIC provides a measure of model quality that balances the trade-off between goodness of fit and model complexity.

2.6 Gap in Profitability and Financial Sustainability Studies

Globally, tools like loss ratio analysis, ruin theory, and linear regression are commonly used to evaluate the viability of insurance products. However, in Kenya's microhealth sector, these tools remain underutilised or inconsistently applied. Most existing literature either lacks access to data or relies on qualitative approaches, limiting comparability and predictive insight. Studies like (Maina, 2021) and (Muriithi et al., 2020) confirm the positive impact of MHI on healthcare utilisation, yet questions remain around its financial viability and long-term profitability.

Many evaluations of micro health insurance in Kenya have focused on operational and community-level factors, often overlooking standardised financial assessment. (Richard, 2024) evaluated sustainability using qualitative indicators such as community uptake, donor support, but did not quantify profitability. Other regional studies, such as (Njuguna, 2012), discuss adverse selection and pricing inefficiencies, yet lack a consistent actuarial framework for measuring financial outcomes.

This study aims to fill this gap by applying actuarial and analytical techniques to assess the profitability and financial sustainability of micro health insurance schemes in Kenya, thereby contributing to more data-driven and sustainable insurance solutions.

3 METHODOLOGY

3.1 Descriptive Statistics

Descriptive statistics refer to sets of values that provide simple summaries of the characteristics of quantitative datasets. The datasets could represent either complete or sample populations.They can be classified into two types:

1. Measures of central tendency
2. Measures of variability

3.1.1 Measures of Central Tendency

They are used to estimate the central value around which a set of values tend to cluster. The most commonly used measures are the arithmetic mean, mode, and median. The most significant measure in this study is the arithmetic mean. The arithmetic mean $\overline{x}$ of a sample of n observations $x_1, x_2, x_3, ..., x_n$ is given by:

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3.1.1}$$

3.1.2 Measures of Variability

They are used to quantify the spread of a set of values, that is, how far apart values lie. The most common measures are range, interquartile range, variance and standard deviation. The unbiased variance s^2 of a sample of $x_1, x_2, x_3, ..., x_n$ observations drawn from a population with variance is given by:

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2 \tag{3.1.2}$$

The standard deviation s of the sample is given by the square root of s^2 .

3.2 Loss and combined ratios

Loss ratio is defined as the proportion of total premiums collected that is dispersed as claims. Its computation provides a basis for assessing whether the insurance scheme is financially sustainable.The loss ratio R_l is given by:

$$R_l = \frac{S}{P} \times 100\% \tag{3.2.1}$$

Where:
S = total claims incurred
P = premiums earned

The combined ratio adjusts the loss ratio by including the expenses accumulated in the process of administering the insurance.
The combined ratio is R_c given by:

$$R_c = \frac{S+E}{P} \times 100\% \tag{3.2.2}$$

Where E = expenses incurred.

3.3 Sensitivity and Scenario Analysis

Sensitivity analysis is a method used to evaluate how changes in key input variables affect a model's output. The aim is to determine which variables substantially affect the outcomes, thereby providing insights to inform decisions.

Scenario analysis, on the other hand, extends this approach by analysing combinations of input changes that represent plausible real-world situations. Instead of altering a single variable, scenario analysis considers a set of assumptions to evaluate the model's behaviour under more holistic conditions.

3.4 Risk Modelling

The risks associated with short-term insurance contracts can be modelled by relatively simple actuarial models. Non-life health insurance can be categorised as short-term because:

1. Policies last for a fixed, relatively short term, usually a year.
2. The insurer receives premiums from the policyholder (lump sum or periodically over the duration of the contract) and, in return, covers any claims brought forward by the policyholder as agreed in the policy over its duration.
3. The policyholder has the option to renew or not renew the policy at the end of the term.
4. The premiums payable for the policy may change from term to term.

Important assumptions are made in short term risk modelling. These are:

1. The number of claims received is independent of individual claim amounts
2. All individual claim amounts are independent.
3. The distribution of the amounts of individual claims is unchanged during the term of the policy.

Short-term risk models can either be collective or individual, depending on the underlying assumptions.

3.4.1 The Collective Risk Model (CRM)

The collective risk model aims to quantify the risk associated with an insurance cover by determining the distribution of S, the aggregate claims, that is, the sum of individual claim amounts. The assumptions made are:

- Claim amounts $\{X_i\}_{i=1}^{N}$ are non-negative, independent and identically distributed random variables.
- The number of claims arising in a period, N, is a random variable and independent of $\{X_i\}_{i=1}^{\infty}$

Therefore:

$$S = \sum_{i=1}^{N} X_i \tag{3.4.1}$$

From this, it can be shown that the cumulative distribution function of S is:

$$G(x) = \sum_{n=0}^{\infty} P(N = n) F^{n*}(x) \tag{3.4.2}$$

Where $F^{n*}(x)$ is the cumulative distribution function of the sum of n X_i terms.
$G(x)$ can be evaluated either exactly or approximately using the moments of S and the Normal and translated Gamma distributions.

3.5 Loss Distributions

Refers to statistical distributions used to model financial losses. The Exponential, Lognormal and Gamma distributions are used in this case.

3.5.1 The Exponential distribution

Is the probability distribution of the time between events in a Poisson process. Characterized by a single parameter λ. The exponential distribution is a special case of the Gamma distribution (when

$\alpha = 1$).
Its probability density (pdf) and cumulative distribution functions (cdf) are given by:

$$f(x;\lambda) = \lambda e^{-\lambda x}, \quad x \geq 0 \tag{3.5.1}$$

$$F(x;\lambda) = 1 - e^{-\lambda x}, \quad x \geq 0 \tag{3.5.2}$$

respectively.
Its mean and variance is given by:

$$\mathbb{E}[X] = \frac{1}{\lambda} \tag{3.5.3}$$

$$\mathrm{Var}(X) = \frac{1}{\lambda^2} \tag{3.5.4}$$

3.5.2 The Lognormal distribution

Is a continuous probability distribution of a random variable whose logarithm is normally distributed.
Its probability density (pdf) and cumulative distribution functions (cdf) are given by:

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right), \quad x > 0 \tag{3.5.5}$$

$$F(x) = \Phi\left(\frac{\ln x - \mu}{\sigma}\right) \tag{3.5.6}$$

respectively.
Its mean and variance is given by:

$$\mathbb{E}[X] = e^{\mu + \frac{\sigma^2}{2}} \tag{3.5.7}$$

$$\mathrm{Var}(X) = \left(e^{\sigma^2} - 1\right) e^{2\mu + \sigma^2} \tag{3.5.8}$$

3.5.3 The Gamma distribution

Is a versatile two-parameter (α, β) distribution. Both parameters are positive real numbers. It is especially effective when the variance exceeds the mean.

Its probability density (pdf) and cumulative distribution functions (cdf) are given by:

$$f(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{\beta x}, \quad x > 0 \tag{3.5.9}$$

$$F(x) = \frac{\gamma(\alpha, \beta x)}{\Gamma(\alpha)}, \quad x > 0 \tag{3.5.10}$$

respectively.
Its mean and variance is given by:

$$\mathbb{E}[X] = \frac{\alpha}{\beta} \tag{3.5.11}$$

$$\mathrm{Var}(X) = \frac{\alpha}{\beta^2} \tag{3.5.12}$$

3.6 Maximum Likelihood Estimation (MLE)

MLE is a method used to estimate the parameters of a statistical distribution by maximizing the likelihood function. Given a sample $\{x_1, x_2, \ldots, x_n\}$ from a distribution with a probability density function (pdf) $f(x;\theta)$, the likelihood function is:

$$L(\theta) = \prod_{i=1}^{n} f(x_i;\theta) \tag{3.6.1}$$

The log-likelihood function is:

$$\ell(\theta) = \log L(\theta) = \sum_{i=1}^{n} \log f(x_i;\theta) \tag{3.6.2}$$

The Maximum Likelihood Estimator (MLE), denoted by $\hat{\theta}$, is the value of θ that maximizes $\ell(\theta)$:

3.7 Akaike Information Criterion (AIC)

AIC is used to compare the relative quality of statistical models for a given dataset. It balances goodness-of-fit with model complexity. The AIC is calculated as:

$$\mathrm{AIC} = 2k - 2\ell(\hat{\theta}) \tag{3.7.1}$$

Where:

- k is the number of estimated parameters in the model
- $\ell(\hat{\theta})$ is the log-likelihood evaluated at the maximum likelihood estimate (MLE)

The model with the lowest AIC is considered the best among the candidates, as it achieves a good fit with fewer parameters.

3.8 Data Simulation

Given the lack of actual data from micro health insurance providers in Kenya, modelling of the financial dynamics and loss ratios associated with the market is done using simulated data. Assuming similarity in cost rates, claims and mortality across different insurers may lead to inaccurate results. Moreover, the available datasets are usually small and insufficient for comprehensive analysis.

A data set containing data collected during the Kenya Household Health Expenditure and Utilisation Survey (KHHEUS) conducted in 2018 is used as a basis for simulating industry data over a period of ten years. The data set is available on the Kenya National Data Archive (KeNADA) website.

3.8.1 Data Consolidation

Families usually enroll in a single health insurance plan that covers every household member. In the data files used, 'clid' represents a scientifically selected area from an Enumeration Area (EA) for the purposes of carrying out household-based sample surveys. On the other hand, 'hhid' denotes a group of people living together under one head, sharing a home and meals. Combining these two variables creates a unique household identifier.

3.8.2 Missing and Extreme Values

The extreme values in the two outpatient columns (outpatient costs and visits) were examined. This is important given that extreme values in these columns, where data was collected only for the last month, could significantly skew annualised medical cost estimates if extrapolated. There are various ways to mitigate this. In health expenditure research, researchers often trim between the upper 0.5% and 20% of the values to reduce outlier influence (Weichle et al., 2013). Therefore, a threshold was set at the 99th percentile and records exceeding this value were dropped.

Missing outpatient costs were filled in using averages based on illness and the type of hospital service the patient received. To justify this, it is necessary to confirm whether medical costs actually differ across these groups. QQ-plots of medical costs suggest that the costs are not normally distributed, and so non-parametric methods are better suited. According to (Nahm, 2016), these methods do not require any distributional assumptions.

The Kruskal-Wallis test is used to justify the imputation. It is the non-parametric equivalent of the ANOVA test and examines independence by testing whether there are statistically significant differences between group medians (Corder and Foreman, 1999). The results indicate that both inpatient and outpatient medical costs vary significantly by the type of service received and by the illness of the patient, therefore justifying the imputation method.

3.8.3 Aggregate and Annual Household Costs

All costs are aggregated by households since health insurance is primarily obtained at the household level. It became evident that some of the surveyed households in the dataset did not have matching medical records. This could be due to errors during the data collection process or, simply, because they did not have any hospital visits during the stipulated time periods. To create a realistic dataset for medical insurance where a policy may not always result in claims over a given period, these 'zero' claims are needed. Therefore, the missing households were identified and their details incorporated with those that have medical records.

To annualise outpatient medical visits and costs, households were grouped based on their wealth index and the number of individuals in a household. Joint kernel density estimates were then fitted within each group, from which the preceding eleven months of costs and visits were sampled. Kernel Density Estimation (KDE) is a non-parametric method used to estimate the probability density function of a random variable (Silverman, 1986) while still preserving the dependence of the variables. To justify this approach, outpatient medical costs and visits should be significantly influenced by household wealth and size. Results from the Kruskal-Wallis test support this claim.

3.8.4 Medical Usage Annualization

The number of hospital visits in a month and medical bills are dependent variables. Joint kernel Density Estimates were fitted within each wealth-size stratum. Each was then sampled eleven times to generate data for every individual over the preceding year. These simulated values were then combined with the observed data from the final month to estimate each household's annual medical visits and expenditure.

Given a set of observed values $\{x_1, x_2, \ldots, x_n\}$, the kernel density estimator $\hat{f}(x)$ at a point x is defined as:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{3.8.1}$$

Where:

- n is the number of observations
- $h > 0$ is the bandwidth (automatically determined in this case)
- $K(\cdot)$ is the kernel function, a symmetric, non-negative function that integrates to one
- x_i are the observed data points

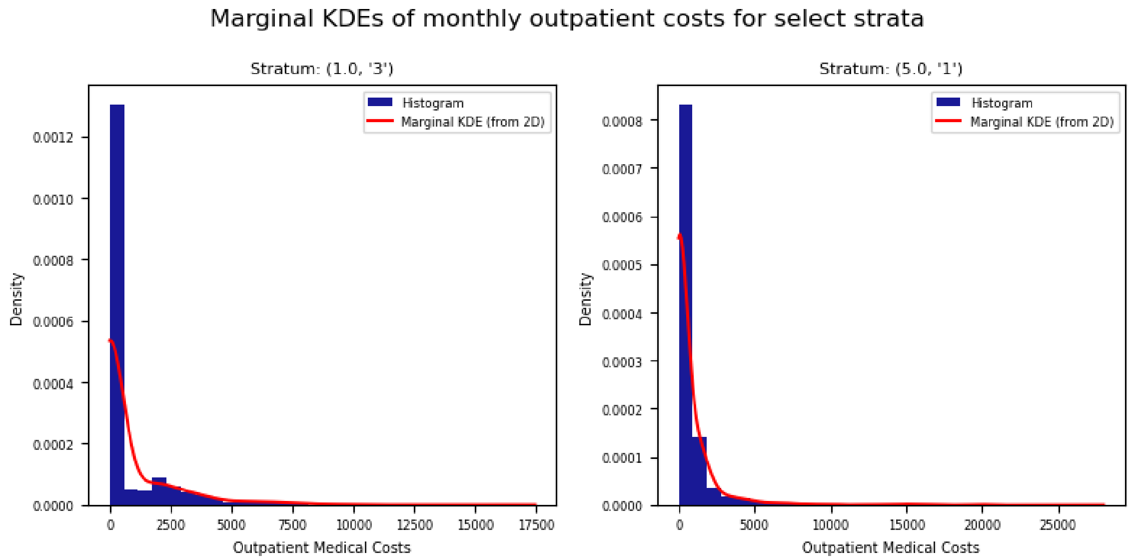


Figure 3.1: Marginal KDEs of monthly outpatient costs

Similar to the previous step, joint kernel density estimates were fitted within each wealth–size stratum and ten samples were drawn per individual to simulate yearly medical expenditures over a ten-year period. These simulated annual values assume that spending patterns, household composition, and financial status remain constant throughout the period.

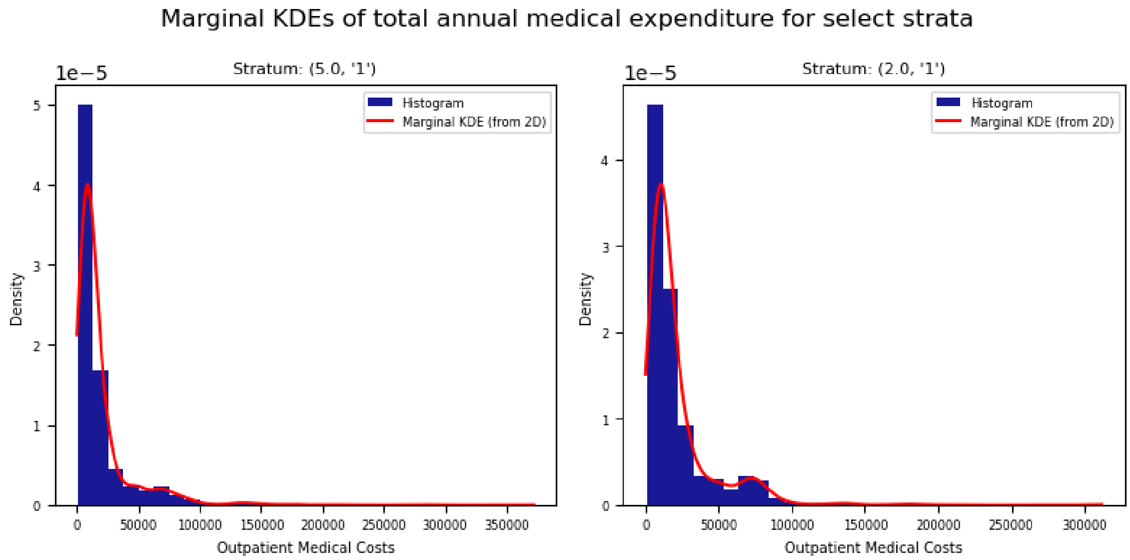


Figure 3.2: Marginal kdes of total annual medical expenditure

The data may not accurately depict the challenges of the low-income populations. However, statistical models and distributions are applied to ensure the generated data is accurate in representing the financial characteristics of micro health insurance schemes. This approach provides a realistic depiction of the risk dynamics within the market.

4 ANALYSIS AND FINDINGS

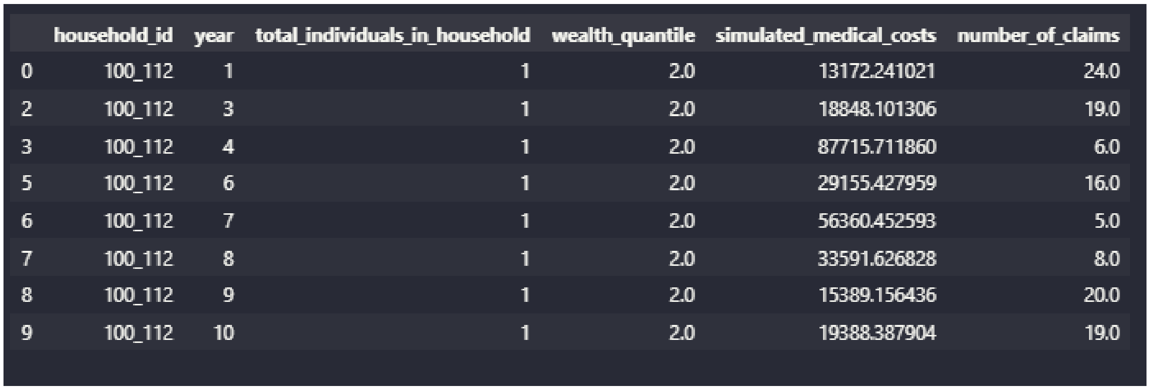
4.1 Data description and summary statistics

The simulated medical costs dataset contains six fields:

- Household id : a unique identifier for every household.
- Year : the specific year, a value between 1 and 10
- Total individuals in household : an integer field detailing the total number of individuals living in the household under one household head.
- Wealth quantile : the household's wealth quantile, a value between 1 and 5, 1 being the poorest household and 5 the wealthiest.
- Simulated medical costs : The households' medical costs for the year.
- Number of claims : The number of hospital visits (claims) that resulted in costs incurred by the family

Distribution by household size		
Household size	**Frequency**	**Percentage of total**
1	6150	47.86
2	4341	33.78
3	2028	15.78
3 or more	330	2.57

Table 4.1: Distribution by household size



	household_id	year	total_individuals_in_household	wealth_quantile	simulated_medical_costs	number_of_claims
0	100_112	1	1	2.0	13172.241021	24.0
2	100_112	3	1	2.0	18848.101306	19.0
3	100_112	4	1	2.0	87715.711860	6.0
5	100_112	6	1	2.0	29155.427959	16.0
6	100_112	7	1	2.0	56360.452593	5.0
7	100_112	8	1	2.0	33591.626828	8.0
8	100_112	9	1	2.0	15389.156436	20.0
9	100_112	10	1	2.0	19388.387904	19.0

Figure 4.1: The simulated data

Since the aim of the project is to examine the sustainability of health insurance aimed at the low-income populations, the data is filtered for households below the wealth quantile 3. Quantile 3 is used as the threshold since any household below it is guaranteed to be living below the average standards of living in the country, and therefore more likely to fit the low-income description.

Of the 12849 households that qualify as low income, nearly 50% are single persons households, while less than 3% contain more than 3 individuals.

The average annual medical costs per household is around Ksh 25400 with a standard deviation of 41048. The average number of claims is 14.31 with a standard deviation of 13.23. The minimum annual medical cost over the ten-year period is Ksh 115 and the maximum is Ksh 2,033,576. 75% of annual medical costs lie below Ksh 27309.

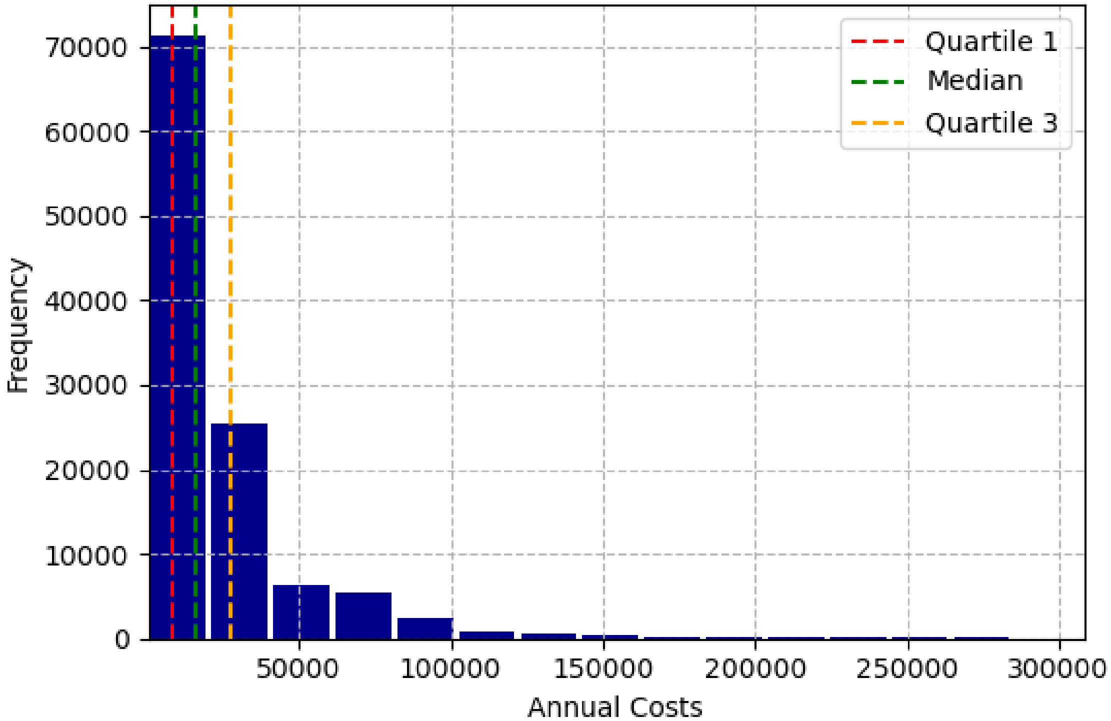


Figure 4.2: Histogram of annual medical costs

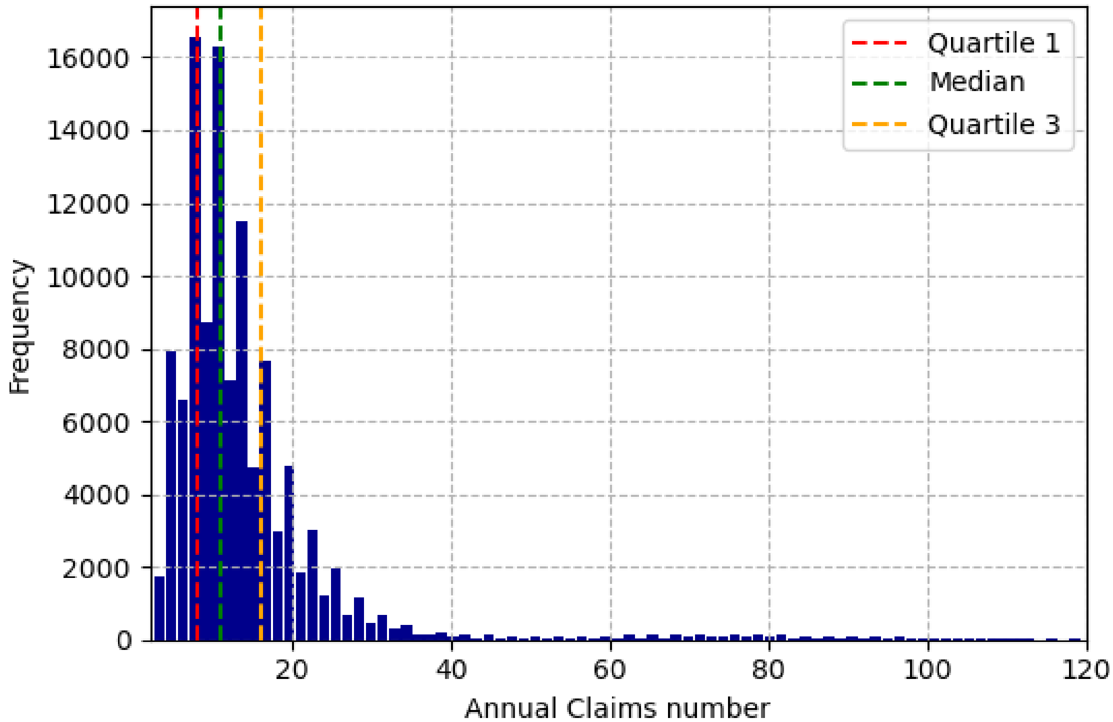


Figure 4.3: Histogram of annual medical costs

4.2 Sensitivity analysis

We use sensitivity analysis to examine the effects of different factors on the profitability of a hypothetical micro-health insurance scheme taken up by the households in the dataset. To accomplish this, in the absence of direct industry data, we analyze the effect of reasonable values for the following factors on the scheme's profitability:

1. Upper limits on the amount of claims the insurer pays.
2. Premium amount.
3. Number of policies.
4. Administrative expenses.

4.2.1 Perfect conditions

The Insurance (Microinsurance) Regulations, Legal Notice No. 26 of 2020, state that the daily premiums for a micro-insurance cover should not exceed forty shillings. This amounts to Ksh 1,200 per month. We can obtain a baseline understanding of the scheme's profitability by setting the premiums at this level for 1000 policies and making the following 'perfect' assumptions:

1. There are no lapses in premium payments
2. No administrative or operational expenses are incurred
3. There are no upper limits on the claims the insurer pays
4. All claims are legitimate and paid out in full by the insurer

Under these conditions, the scheme has an average loss ratio of 157.56% over 10 years.

4.2.2 Upper limits on the liability

Health insurance policies do not offer complete medical coverage. Most schemes impose upper limits on the amounts they are liable to cover, usually distinguishing between inpatient and outpatient benefits. Average loss ratios of 146.98%, 140.00%, and 124.80%, respectively, show a reduction from the initial 157.56%.

Loss ratio (%) at different coverage limits			
Year	**100,000**	**75,000**	**50,000**
1	146.54	138.97	122.34
2	156.88	149.32	131.94
3	153.40	145.44	128.62
4	140.35	134.75	121.66
5	145.00	137.37	123.25
6	143.57	137.37	122.45
7	140.98	135.69	123.44
8	147.09	139.14	123.33
9	155.86	147.05	129.02
10	140.11	134.80	121.91

Table 4.2: Loss ratio percentages at different coverage limits

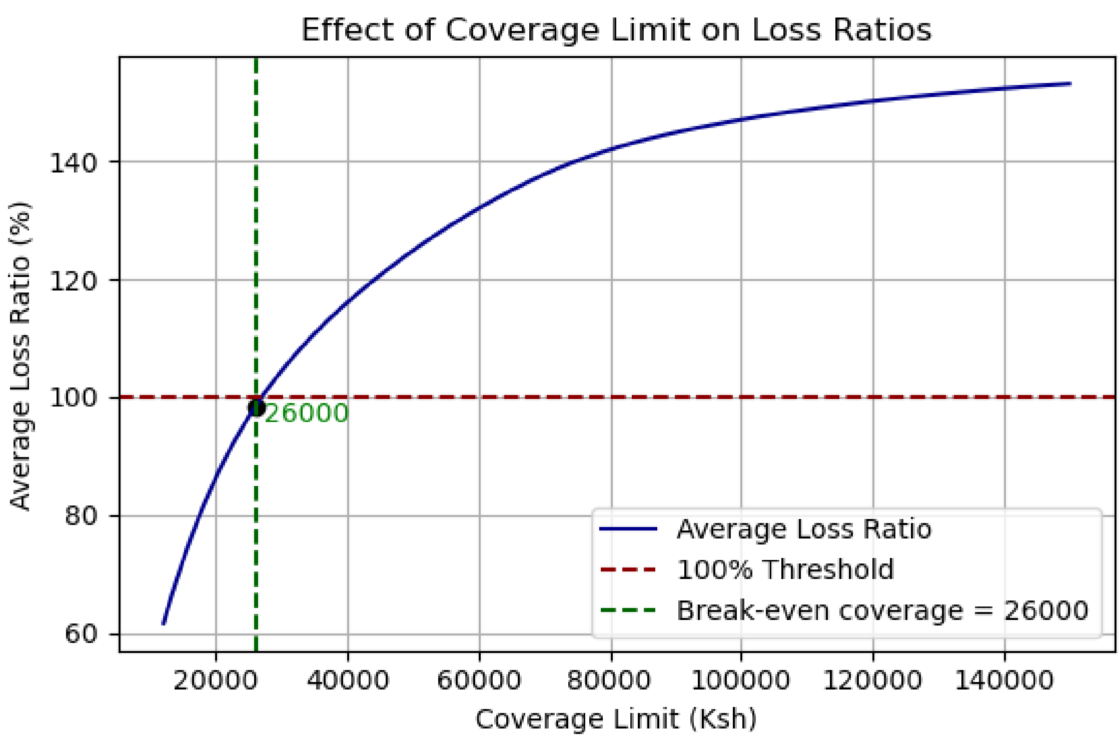


Figure 4.4: Effect of coverage limit on loss ratios

4.2.3 Increased premiums

We examine the effect of increasing the maximum micro insurance premiums of Ksh 1200 by 50%, 100%, and 200% for 1000 policies while maintaining no upper limit on medical costs and ignoring expenses.This approach explores how increasing revenue through higher premiums can improve the insurer's profitability, even with the same exposure to high medical costs.

Loss Ratio (%) with Increased Premiums			
Year	**+50% Premium**	**+100% Premium**	**+200% Premium**
1	103.72	77.79	51.86
2	112.00	84.00	56.00
3	113.90	85.42	56.95
4	99.80	74.84	49.90
5	101.97	76.48	50.98
6	101.63	76.22	50.81
7	98.24	73.68	49.12
8	105.04	78.78	52.52
9	114.72	86.04	57.36
10	99.40	74.55	49.70

Table 4.3: Loss ratio percentage with increased premiums

A 50% increase in premiums raises the standard premium by 50% to 1800. As a result, loss ratios are reduced. A 100% premium increase significantly reduces the loss ratio, bringing some years close to breakeven. Increasing the premiums by 200% lowers to below 100%.

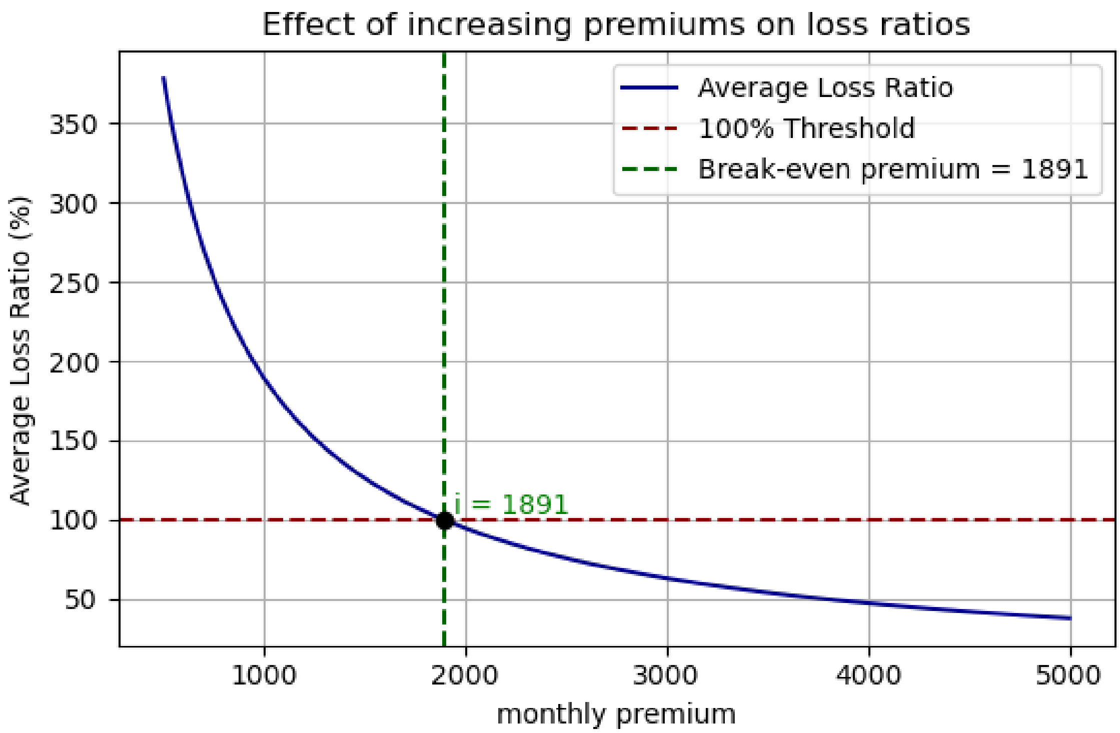


Figure 4.5: Effect of increasing premiums on loss ratios

4.2.4 Number of policies

Here, we explore the effect of increasing the number of active policies (100%, 500%, 1000%) on base scheme profitability. Increasing the number of customers can enhance premium income, but it also increases claim exposure.

Loss Ratios (%) with Increased Customers			
Year	**+100% Customers**	**+500% Customers**	**+1000% Customers**
1	149.98	153.80	156.26
2	162.81	155.43	156.10
3	159.45	154.92	153.92
4	155.52	156.71	155.11
5	149.26	156.94	158.49
6	148.85	156.01	153.66
7	149.40	153.14	153.34
8	155.80	157.86	158.06
9	161.21	157.31	154.26
10	156.13	159.13	157.42

Table 4.4: loss ratio percentage with increased customers

A 100% increase in policies to 2000 results in loss ratios ranging from 148.85% to 162.81%, with an average of 154.84%. A 500% increase in policies causes loss ratios to worsen, ranging from 153.14% to 159.13% with an average of 156.1%. With a massive customer base, the loss ratios slightly improve, averaging around 155.66%

4.2.5 Administrative Expenses

Here, we look at the effect of varying expense amounts as percentages of claims collected on baseline scheme profitability. Average combined ratios rise from 157.56 in the baseline scheme to 173.32 to 204.83 to 236.34 as different percentages of proportions are introduced. A 20% increase in administrative costs and expenses leads to a 32% increase in the combined ratios.

4.3 Scenario analysis

In the previous section, we've discussed and outlined the effects of different factors in isolation on the baseline scheme's profitability. However, to accurately capture the complexity of these effects in a real world scenario, they need to be considered in tandem. For instance, a coverage limit of

Combined Ratios (%) at Different Expense Amounts			
Year	**10% of Claims**	**30% of Claims**	**50% of Claims**
1	171.14	202.26	233.38
2	184.80	218.40	252.00
3	187.93	222.10	256.27
4	164.66	194.60	224.54
5	168.24	198.84	229.42
6	167.68	198.17	228.66
7	162.10	191.57	221.04
8	173.31	204.82	236.33
9	189.29	223.70	258.12
10	164.01	193.83	223.65

Table 4.5: Combined ratio percentage at different expense amount

Ksh 75000 and a 150% increase in premiums could create a sufficient buffer such that a scheme remains profitable even after having a 30% increase in its expenses and costs

Most Profitable Scenarios			
Coverage Limit (Ksh)	Premium percentage increase	Expense Rate (as a proportion of claims)	Average Combined Ratio (%) over 10 years
50,000	300	0.1	45.76
75,000	300	0.1	51.34
100,000	300	0.1	53.89
50,000	300	0.3	54.08
75,000	300	0.3	60.67

Table 4.6: Most profitable scenarios

Least Profitable Scenarios			
Coverage Limit (Ksh)	Premium percentage increase	Expense Rate (as a proportion of claims)	Average Combined Ratio (%) over 10 years
75,000	150	0.3	121.34
50,000	150	0.5	124.80
100,000	150	0.3	127.38
75,000	150	0.5	140.00
100,000	150	0.5	146.98

Table 4.7: Least profitable scenarios

4.4 Evaluation of the 'best-case scenario' using the Collective Risk Model (CRM)

We choose the scheme with coverage of Ksh 100,000, a 300% increase in premiums and expenses amounting to 50% of claims as the best-case scenario to make loss approximations for. An annual health insurance coverage of Ksh 100,000 is more than enough to cover the annual medical costs of more than 80% of the households in the dataset. A monthly premium of Ksh 3600 provides a large enough income to cover costs and expenses (the average combined ratio is 73.48%) and the expenses are conservative enough to cover a reasonable amount of costs that may be incurred in administering the policy.

Given that the annual aggregate medical claims, S, is a random variable, it's possible to obtain the probability that S exceeds a particular value x, i.e. Pr (S ¿ x). This can help us quantify the probability of an insurer making a loss given a certain premium and income level. Since expenses are function of S in this case, the probability of making a loss becomes:

$$\Pr(S + 1.5S > \text{Total Premiums})$$

$$\Pr(1.5S > \text{Total Premiums})$$

Taking the baseline risk set of 1000 policies where a monthly premium of Ksh 3600 (300%-increased base premium of 1200) is paid without fail for 12 months:

$$\Pr(1.5S > (3600 \times 12)1000)$$

$$\Pr(1.5S > 43,200,000)$$

$$\Pr(S > 28,800,000)$$

To find the probability of making a loss, the distribution of S is needed. We let Since each X_i is non-negative and presumably independent of other X_i values, the distribution of S can be determined by the collective risk model:

$$S = \sum_{i=1}^{1000} X_i$$

For a large number of X_i , it's reasonable to approximate the distribution of S from its mean and variance using the standard normal distribution. The mean and variance of S in this case is given by:

$$E(S) = \sum_{i=1}^{1000} E(X)$$

$$V(S) = \sum_{i=1}^{1000} V(X)$$

We therefore need to identify the distribution of X and its moments in order to identify those of S. The most common loss distributions for claims amounts are the exponential, lognormal and gamma distributions. The parameters are estimated from the data using maximum likelihood estimate as follows:

Distribution	Parameter	Value	AIC score
Exponential	λ	0.00004207	19654.6925
Lognormal	μ	9.6009	19705.2748
	σ	1.0861	
Gamma	α	1.1908	19646.8240
	β	0.00005966	

Table 4.8: Distribution Fitting Results

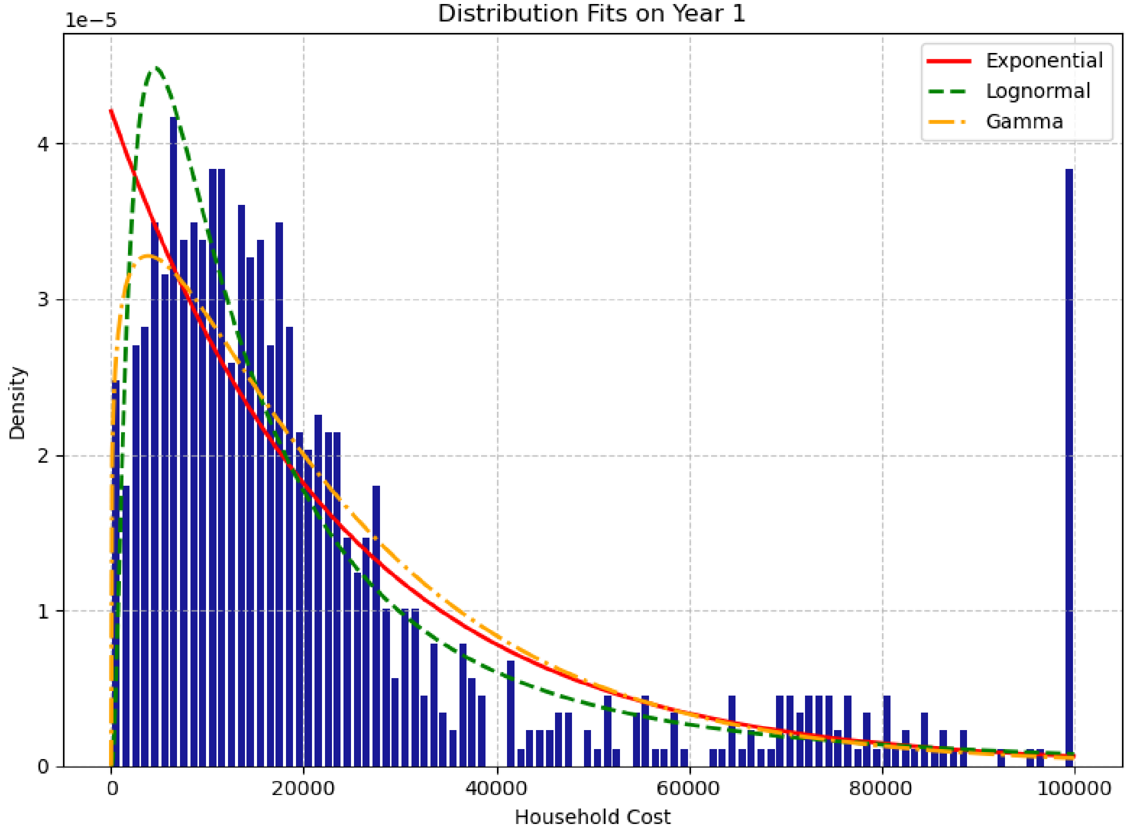


Figure 4.6: Distribution fitting results

The gamma distribution provides the best fit for the data since it has the lowest AIC score. The mean and variance of X are thus given by:

$$\mathbb{E}[X] = \frac{\alpha}{\beta} = \frac{1.1908}{0.00005966} = 19{,}959.77$$

$$\mathrm{Var}(X) = \frac{\alpha}{\beta^2} = \frac{1.1908}{(0.00005966)^2} = 334{,}558{,}700$$

Therefore:

$$\mathbb{E}[S] = 1000 \times 19{,}959.77 = 19{,}959{,}770$$

$$\text{Var}(S) = 1000 \times 334{,}558{,}700 = 3.346 \times 10^{11}$$

The probability of loss can be estimated as:

$$1 - \Pr(S \leq 28{,}800{,}000) = 1 - \Phi(z)$$

Where:

$$z = \frac{28{,}800{,}000 - \mathbb{E}[S]}{\sqrt{\text{Var}(S)}}$$

$$z = 15.28$$

$$\Phi(15.28) = 1$$

Therefore, the probability of loss $P = 0$

Given the low probability of loss, it's evident that there is room for further adjustments to the best case scenario:

Upper limit of Ksh 500,000 in benefits	
Premium amount	**Probability of loss**
3600	0
3400	0
3200	0.0034
3000	0.3136
2800	0.9585

Table 4.9: Upper limit of Ksh 500,000 in benefits

Upper limit of Ksh 1,000,000 in benefits	
Premium amount	**Probability of loss**
3600	0
3400	0
3200	0.005
3000	0.3564
2800	0.9671

Table 4.10: Upper limit of Ksh 1,000,000 in benefits

5 DISCUSSION AND FINDINGS

5.1 Optimal Conditions and Coverage Limits

This section explains the key findings from the observations made under the data analysis and findings section. Even if we assume 'perfect' conditions as described in chapter 4, the scheme remains unprofitable, with an average loss ratio of 157.56% over 10 years. This suggests that, on average, for every Ksh 1 of premium received, the insurer pays out Ksh 1.57 in claims, a situation that would lead to significant losses and eventually, insolvency.

As mentioned before, most schemes set a cap for the amount they intend to cover. At overall coverage limits of Ksh 100,000, 75,000, and 50,000, this particular scheme remains unprofitable. Average loss ratios of 146.98%, 140.00%, and 124.80%, respectively, show a reduction from the initial 157.56% but are still too high to make the scheme viable while providing a reasonable level of cover for customers.

5.2 Level of Premiums

The maximum allowable premium of Ksh 1,200 per month is insufficient to cover a majority of household medical expenses. This is because the scheme results in losses at various coverage levels, even before accounting for administrative costs. This may explain why, for instance, the Linda Jamii micro-health insurance program by Britam and Safaricom, which offered a comprehensive cover of Ksh 290,000 for premiums of Ksh 1,000 per month, was discontinued.

Different premium level increases have varying effects on the performance of the scheme. A 50% premium increase translates to more premium income per policy, but the insurer still faces unlimited medical cost exposure. On the other hand, a 100% premium increase brings some years close to break even. This suggests that doubling premiums provides a buffer against high claims. However, the buffer may not be sufficient in a real world scenario since the inclusion of other factors such as expenses and administration costs may inflate the costs and lead to losses.

In a scenario where there is a 200% premium increase, premium income is sufficient to cover claims. This scenario is the most profitable. This shows that higher premiums are critical for sustainability when unlimited claims are allowed.

These results indicate that health micro-insurance in its current form is almost completely unfeasible. The insurer either has to offer meagre benefits, which may not attract a lot of customers, or, at the very least, double the premiums and try to minimize operational costs in order to make a profit, which may alienate the target audience due to unaffordability.

5.3 Operational Expenses and Policy Numbers

Unlike the other factors, quantifying the effects of the number of policies on profitability is not as straightforward. An increase in policies results in increases in both revenues and claims filed, making it hard to delineate the effects on loss ratios effectively.

Naturally, since the expenses are calculated as a function of the claims, it's expected that an increase in the percentage would lead to an increase in combined ratios, and therefore less profitability.

5.4 Scenario analysis

The most profitable scenarios are those involving a 300% premium increase while the least profitable ones involve the lowest premium increase of 150%. The insurer is almost always doomed to make losses for any premiums less than Ksh 2400. Provided expenses are kept lower than 10% of the claims paid out and the premiums increase is greater than 200%, the scheme is always profitable, even at the maximum coverage levels of Ksh 100,000.

Having expenses less than 10% of claims results in profitable combined ratios in all but two out of nine scenarios. This hints at an important factor in micro-health insurance profitability. Given that the premiums have to be low to attract low income populations, the forgone income in terms of premiums can be recovered by streamlining administrative processes and lowering costs to ensure that a scheme turns a profit.

5.5 Evaluation of the 'best-case scenario'

It is important to quantify the probability and frequency at which losses, if any, are expected to occur. This is despite the fact that the best-case scenario is proven to be profitable on account of having average loss ratios significantly less than 100%. The gamma distribution is found to be the best candidate out of the three common loss distributions for modelling household claim amounts. The normal approximation is used due to the simplicity and ease of obtaining standard normal probabilities. However, it has its drawbacks. The normal distribution has zero skewness, and has a distribution that goes to zero very quickly. For many types of insurance, the distribution of S is positively skewed (Dickson, 2016).

It should be noted that none of the distributions can model the spike in claims at the Ksh 100,000 mark caused by the coverage limit. Thus, that the probability of loss is found to be zero should only be considered as indicative of the strength and stability of the best-case scenario scheme. Given complete real world data, the probability would change. First, the assumption used is that all the premiums are paid in full, which would not happen in the real world, especially in a scheme geared at the low income population where rates of premium defaults are high. Second, although the expenses used are relatively conservative, an insurer's expenses may significantly exceed or fall below 50% of claims depending on how the company is run and the efficiency of operation.

After subsequent adjustments to the best case scenario, it is evident that the benefits can be extended up to a million Kenyan shillings. This is important since for a micro-health insurance product to remain competitive and attract customers, it needs to offer coverage benefits that are on par, at the very least, with industry norms. For instance, the discontinued Linda Jamii micro-health insurance scheme by Britam and Safaricom offered benefits of up to Ksh 290,000. At both coverage levels, premiums could be dropped to as low as Ksh 3200 while still maintaining a high probability of profit.

5.6 Comparison With Existing Literature Materials

In order to draw a valid and unbiased conclusion, the obtained results have to be compared to existing, published figures. The 'perfect conditions' scheme has an average loss ratio of 157.56% over the ten-year period. An insurance firm that has a loss ratio of more than 100% is not profitable (Mugo et al., 2023,). This particular scheme has a loss ratio far above the recommended value and is therefore not profitable, with loss ratio as the measuring unit.

Putting a limit on the amount of claims to be covered is a delicate process. For a microinsurance company, the maximum benefit chosen directly drives the loss ratio and ultimately, the scheme's financial sustainability. According to (Angove and Dalal, 2014), capping annual claims helps a microinsurance provider to implement claims control and reduce unrecorded claim payments. Assigning different caps to this particular scheme's benefit payments therefore gives a clear picture of how limiting payouts affects both the level of protection offered and the insurer's risk exposure.

Legal frameworks directly influence the microinsurance environment in Kenya.Existing laws dictate the daily premiums for a microinsurance cover should not exceed forty shillings(The Insurance Act, 2020). This amounts to about Ksh 1,200 per month. However, studies of Kenyan household health spending report monthly OOP medical expenses far above what the regulatory ceiling can cover. Consequently, at the ksh 1200 premium cap insurers cannot collect sufficient revenue to match typical claims costs. The scheme remains unprofitable and would operate at a substantial loss if implemented under current regulations.

The percentage of policyholders who discontinue their coverage over a given period is crucial. However, it is not a factor that should be used to determine the profitability of a microinsurance scheme on its own. A study carried out on microinsurance service providers showed that a large percentage of providers considered policy lapse a minor risk (Njuguna and Arunga, 2013). Setting the lapse rate at 25% and 50% is suitable for this particular scheme as it captures the worst possible but reasonable scenarios, especially given the fact that the lapse rate for non-life insurance in Kenya stands at 12% (Christopher, 2024).

6 CONCLUSIONS AND RECOMMENDATIONS

This study set out to assess the long-term profitability of micro-health insurance in Kenya using actuarial and analytical methods. Based on a comprehensive analysis of loss ratios, scenario testing, and risk modelling, the findings clearly show that the current structure of micro-health insurance schemes is financially unsustainable under existing regulatory and economic conditions.

The average loss ratio of 157.56% over a 10-year period,even under perfect conditions,demonstrates severe underwriting deficits. The results from coverage caps and varying premium structures show that, unless premiums are at least doubled and administrative expenses strictly controlled i.e ¡10% of claims, micro-health schemes are likely to continue incurring losses. These findings directly address the first and second secondary objectives evaluating underwriting performance and testing scheme sustainability under different assumptions.

Scenario and sensitivity analyses further reveal that profitability only becomes attainable under extreme adjustments such as 200%–300% premium increases. This supports the third objective to test the impact of claim frequency, liability, and premiums on profitability and reinforces that achieving balance between affordability and sustainability remains a major challenge.

Risk modelling, particularly using the gamma distribution for claims and the normal approximation for aggregate risk, proved effective in evaluating the financial viability of the best-case scenario. Although this scenario shows profitability, its assumptions such as full premium compliance and minimal expenses are idealized and unlikely to hold in practice. This satisfies the fourth objective utilizing actuarial risk models to project best-case outcomes.

In conclusion, while micro-health insurance has the potential to expand healthcare access for low-income populations, this study confirms that without substantial reform and actuarially sound strategies, it cannot be sustained. Regulatory limitations on premiums, high claim volatility, and operational inefficiencies all contribute to financial imbalance. However, through realistic pricing, cost containment, tiered benefit structures, and public-private collaboration, a practical and profitable micro-health insurance model in Kenya is achievable.

6.1 Recommendations

To align with the study's aim of identifying actuarially sound strategies for improving sustainability, the following are recommended:

- **Review and Reform Regulatory Premium Limits-** The current legal cap of Ksh 1,200 per month is insufficient to sustain comprehensive micro-health insurance. Regulatory reforms should consider raising or indexing the premium ceiling based on inflation and average medical costs, allowing insurers to price more realistically.
- **Implement Tiered Coverage and Premium Models-** Introduce tiered benefit plans (e.g., Ksh 50,000, 100,000, and 250,000) paired with corresponding premiums. This ensures inclusivity while aligning risk exposure with income capacity and helps stabilize underwriting results.
- **Optimize Operational Efficiencies-** Ensure expenses remain below 10% of claims. This can be achieved by digitizing operations, automating claims processing and leveraging mobile platforms for enrolment and premium collection.
- **Adopt Flexible Payment and Policy Renewal Structures-**Use mobile money-based micro payment systems and allow flexible payment intervals reducing lapses and encouraging continuity among low-income earners.
- **Apply Actuarial Risk Models for Pricing and Reserving-**Continue applying models such as the gamma distribution for claim size modelling and the normal approximation for aggregate claims. This provides a statistically sound basis for estimating loss probabilities and setting premium levels.
- **Encourage Public-Private Partnerships-** Encourage collaboration between insurers, government, and NGOs to subsidize premiums for the most vulnerable groups, thereby enhancing affordability without compromising sustainability.

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