DEVELOPING RISK MANAGEMENT MODELS ASSOCIATED WITH LIFE EXPECTANCIES IN THE INSURANCE INDUSTRY

SCHOOL OF PURE AND APPLIED SCIENCES

DEPARTMENT OF MATHEMATICS STATISTICS & ACTUARIAL SCIENCE

by

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REG: P107/2098G/21

RESEARCH PROPOSAL SUBMITTED TO THE SCHOOL OF PURE AND APPLIED SCIENCE IN PARTIAL FULFILMENT OF THE REQUIEMENTS FOR THE AWARD OF THE DEGREE OF BACHELOR OF SCIENCE IN ACTUARIAL SCIENCE

DECLARATION

This proposal is my original work and has not been presented for a conferment of any degree program in any other University.

Name…………………………………………… .ADM……………………………………

Signature………………………………. Date…………………………………

Declaration by the supervisor

This project has been submitted for review with my approval as the University supervisor

Name…………………………………………………

Signature………………………………… Date…………………………………

DEPARTMENT OF MATHEMATICS, STATISTICS AND ACTUARIAL SCIENCE

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KARATINA UNIVERSITY

Dedication

I dedicate this research proposal to God Almighty, our creator, sustainer, our source of inspiration and wisdom. He has been the sole source of my strength throughout this entire study and it is with his degree and favor that I have successfully undertaken this study.

I also dedicate this work to both my parents who continually encourages and support me, morally, materially and spiritually to make sure that I give it all it takes to finish that which I have commenced. Thank you very much you can never be quantified. God bless you all abundantly.

ACKNOWLEDGMENT

I am grateful to Almighty God for giving me the opportunity, strength, dedication and determination to make this research paper success.

Special thanks to my supervisor Dr. Ngigi for the patient guidance, encouragement and unwavering support he has provided throughout the study. I am extremely lucky to have a supervisor who cares so much about my work and who respond to my questions promptly and satisfactorily.

ABSTRACT

This research aims to develop advanced risk management models to address the financial challenges posed by increasing life expectancies in the insurance industry. With the continuous rise in life expectancy due to improvements in healthcare, nutrition, and living conditions, traditional mortality models have become less reliable, leading to significant financial risks for insurers. These risks include increased annuity and pension liabilities, higher healthcare costs, and regulatory pressures to maintain adequate capital reserves. To address these challenges, this study employs the Lee-Carter Model, a widely recognized stochastic mortality model, to forecast mortality trends and assess longevity risk. The model will be applied to data collected from online sources, focusing on the Kenyan insurance industry.

The study seeks to enhance the ability of insurance companies to predict and mitigate longevity risk by incorporating both demographic and economic factors into the modeling process. The research will analyze existing mortality models, identify their limitations, and propose enhancements to improve their predictive accuracy. By doing so, the study aims to bridge the gap between theoretical models and real-world applications, providing insurers with more reliable tools to manage financial risks associated with increasing life expectancies.

The findings of this research are expected to have significant implications for the insurance industry, particularly in the areas of pricing strategies, reserve management, and risk transfer. By improving the accuracy of mortality forecasts, insurers can better anticipate future liabilities, adjust their pricing models, and ensure financial stability in the face of rising life expectancies. The study also contributes to the broader academic discourse on longevity risk management by addressing gaps in existing models, particularly their failure to account for medical advancements, pandemics, and lifestyle changes.

Here is an overview of several models that have been used to forecast mortality risk, along with their respective drawbacks. These models have been widely studied in actuarial science and demography, and each has its strengths and limitations. References to key studies and literature are included where applicable.

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CHAPTER ONE: INTRODUCTION

BACKGROUND OF THE STUDY

The insurance industry plays a critical role in understanding and mitigating longevity risk which is one of the most significant risk insurers face. Longevity is the risk that policyholders will live longer than expected thus influencing the risk and premium of life and pension products. Its key driver is mortality rates. Recently, there has been a rise in life expectancies due to improvements in environmental conditions such as nutrition, housing, sanitation, medical and social services. This has impacted insurance companies to develop effective risk management models to ensure financial stability and sustainability. It has now become difficult to predict mortality trends which has resulted to continuous evolution of risk management techniques with traditional methods failing to capture emerging mortality trends hence creating a gap between expected and actual outcomes.

This study seeks to enhance the risk management strategies of insurance companies in response to increasing life expectancies, so as to improve insurers' ability to anticipate and mitigate longevity risk.

There have been previous studies exploring risk management models in the context of life expectancy and longevity risk. For example, a functional study by the Society of Actuaries (SOA 2021) titled *Longevity Risk Quantification and Management* where the report emphasized on the importance of predictive modelling in mortality trends, advocating for dynamic models that integrate medical and socioeconomic factors. However, existing models often fail to adapt quickly to new longevity patterns, creating a gap that this research aims to address.

Furthermore, the paper *A Simplified Model for Measuring Longevity Risk for Life Insurance (Springer, 2023)* presents a dynamic mortality model designed to improve longevity risk forecasting. By addressing stochastic variations in mortality, the model provides a flexible approach to risk assessment. However, the study does not fully incorporate external, economic and demographic variables, which are crucial in actuarial risk management.

There has been extensive research in longevity risk assessment and mortality modelling but still several gaps remain such as;

- Existing models mainly focusing on demographic trends but not considering financial and economic changes.
- Many models fail to focus on mortality shifts caused by medical advancements, pandemics or lifestyle changes.

The study is essential for developing improved models, enhancing insurers to predict future liabilities, adjust pricing strategies for future purposes which will eventually ensure financial stability. It aims to bridge the gap between modelling and real world applications and insurers will have the necessary tools to effectively manage longevity risk.

PROBLEM STATEMENT

With the rise in life expectancies, the traditional models used in pension and insurance schemes are becoming less reliable. This results in funding gaps and unanticipated liabilities for institutions relying on outdated mortality assumptions. Thus, there is a pressing need for updated models that account for the financial risks tied to longer life spans. This research seeks to address these gaps by developing models that can anticipate the effects of longevity on financial obligations.

This research will analyze existing models, propose enhancements, and test their applicability in the insurance market.

Objectives of the Study

General Objective:

To develop models and techniques to assess and manage financial risks associated with increasing life expectancies.

Specific Objectives:

To identify the primary financial risks associated with increased life expectancy.

To model and forecast mortality risk.

To analyze techniques for managing and mitigating financial liabilities resulting from longevity risk.

Research Questions

What are the main financial challenges posed by increasing life expectancies?

How can statistical and stochastic models improve predictions related to longevity risk?

What strategies can institutions adopt to mitigate the financial impacts of increased life expectancy?

Justification of the Study

The relevance of this study lies in its potential to equip financial institutions with reliable tools to address longevity risk. As life expectancy continues to increase, the study's insights could be pivotal in ensuring that pension and insurance systems remain financially viable, ultimately benefiting society by protecting the economic stability of retirees and policyholders.

According to Association of Kenya insurers (AKI) 2015 report over 65% of the claims incurred in Kenya insurance companies since 2011 were as a result of ordinary life and pensions therefore a need to study mortality and longevity risk concurrently.

Scope of the study

This study will focus on the financial risks and modeling strategies associated with life expectancy trends in the insurance industry, using secondary data from existing actuarial studies and public health records.

The study will enhance the ability of insurance companies to predict, assess and mitigate longevity risk.

Limitations of the study

- Data access and quality; it will be difficult to obtain reliable data and some
  mortality databases may have incomplete or outdated databases.
  Geographical limitation; focused on Kenyan insurance industry thus findings will not be directly applicable to other markets with different demographic and economic conditions.

Financial risks associated with increasing life expectancies

1. Longevity risk; this is the risk that policyholders live longer than expected, leading to higher payouts for life insurance, annuities and pensions. Insurers will be obligated to pay benefits for extended periods, thus make unplanned payments.
2. Annuity and pension liabilities; these contracts for policyholders will last longer than the expected amount of time.
3. Healthcare and long term care insurance risks; the healthcare costs for policyholders will rise thus long term care claims due to increased life expectancies.
4. Reinsurance and risk transfer costs; due to longevity risk, insurers decide to transfer some of their liabilities to reinsurers to solve their unexpected claims but it comes at a cost thus impacting the financial performance of insurance companies.
5. Regulatory and Solvency Risks; Solvency II and IFRS 17 require insurers to hold adequate reserves for longevity risks. This means increasing life expectancies force insurance companies to increase capital reserves reducing profitability.

LITERATURE REVIEW

This Literature Review explores existing research on mortality forecasting models, longevity risk, and their applications in the insurance industry. The review focuses on the Lee-Carter Model, the Renshaw & Habernam Model, the Cairns-Blake-Dowd Model, highlighting their strengths, limitations and their relevance to managing longevity risk, particularly in the context of increasing life expectancies. Additionally, the review will also discuss the findings of the Association of Kenyan Insurers (AKI) 2015 report on claims incurred in the Kenyan insurance companies, which will highlight the importance of mortality and longevity risk management. The review will also highlight the gaps in the literature and demonstrate how the study will contribute to addressing these gaps.

The Lee-Carter Model, which was introduced by Lee and Carter (1992), is one of the most widely used model in mortality forecasting. It decomposes mortality rates into age specific and time specific components, allowing for the projection of future trends. The model is praised for its simplicity and flexibility. However, it has its own limitations such as its assumptions of linear mortality and its inability to account for sudden shocks like pandemics

(Chen & Cox, 2009). Other models such as the Cairns-Blake-Dowd (CBD) Model (Cairns etal., 2006) and Renshaw-Habernam model (Renshaw & Habernam, 2006) offer alternative approaches but are often more complex and computationally intensive. Despite its limitations, the Lee-Carter Model remains a foundational tool for mortality forecasting and is well suited for the study due to its adaptability and proven track record.

The Renshaw & Habernam Model extends the Lee-Carter Model by incorporating cohort effects, which capture generational difference in mortality patterns. This model is useful for analyzing long term mortality trends and has been applied in various contexts, including life insurance and pension schemes. For example, Ngugi & Ochieng (2020) used this model to forecast mortality rates for life insurance in Kenya, demonstrating its ability to improve the accuracy of mortality projections. However, the model's complexity and potential for overfitting makes it less accessible particularly in markets with limited data. Despite its limitations, this model provides valuable insights into cohort-specific mortality trends which are relevant in managing longevity risk.

The Cairns-Blake-Dowd (CBD) developed by Cairns et al. (2006) is a two-factor model that focuses on mortality trends at older ages making it particularly suitable for pension and annuity pricing. The model captures age specific mortality trends and allows for the inclusion of cohort effects, providing a more nuanced understanding of mortality patterns. Mwangi & Mutua (2019) applied the CBD Model to assess longevity risk in Kenyan Pension Schemes, highlighting the ability to project future mortality rates and inform reserve management strategies. However, the model is less effective at capturing mortality trends for younger age groups and does not explicitly account for external factors such as medical advancements or socioeconomic changes. Despite these limitations, the CBD Model remains a valuable tool for managing longevity risk in pension and annuity products.

Longevity Risk is defined as the risk that policyholders live longer than expected and possess a significant challenge for insurers and pension providers. Increase in life expectancies results to insurers facing higher payouts for annuities and pensions thus leading to unanticipated liabilities (Mwangi & Mutua, 2019). Mortality forecasting models, such as the Lee-Carter Model play a crucial role in managing this risk by enabling insurers to predict future mortality trends thus able to adjust their pricing and reserve strategies accordingly.

The AKI 2015 report on claims incurred in Kenyan insurance companies provides valuable insights into the impact of mortality and longevity risk on the local insurance industry. According to the report, over 65% of claims incurred by Kenyan insurers between 2011 and 2015 were related to ordinary life and pension products, thus showing the importance of effective mortality and longevity risk management. The report highlights the need for accurate mortality forecasting models to ensure financial stability of insurers and also protect policyholders. The findings are highly relevant to the study, which seeks to develop improved risk management models for the Kenyan insurance industry in relation to increased life expectancies.

In Kenya, the Lee-Carter Model has been applied to analyze mortality trends and life expectancies. A good example is Odhiambo & Weke (2018) who used this model to project mortality rates and found that life expectancy has been increasing due to improvements in healthcare and living conditions. However, the study also noted that the model struggles to capture sudden mortality shocks, such as those caused by pandemics or economic crisis. Similarly, Mwangi & Mutua (2019) applied the CBD Model to assess longevity risk in Kenyan pension schemes, highlighting the need for more robust models that can account for non-linear trends and external factors. These studies demonstrate the applicability of mortality models in Kenya but also reveal gaps in their ability to address emerging challenges.

There has been extensive research on mortality forecasting and longevity risk but several gaps still remain. Models including the Lee-Carter Model fail to incorporate external factors such as medical advancements, pandemics or socioeconomic changes (Richman & Wuthrich, 2020). On the contrary, there is also limited application of these models in the Kenyan Insurance industry, particularly in the context of increasing life expectancies. These traditional models have provided a solid foundation but they need to be more advanced so as to enhance their predictive accuracy. This study aims to address these gaps by proposing an enhanced version of the Lee-Carter Model tailored to the Kenyan context.

In conclusion, the Literature review highlights the importance of mortality forecasting models mainly focusing on the Lee-Carter Model in managing longevity risk in the insurance industry. This model has been widely applied in the Kenyan context but it has failed to account for external factors and has been underutilized in the country. This study seeks to address these gaps. Eventually, the research will contribute to the development of a more robust management strategies and ensure the financial stability of insurers in relation to increasing life expectancies.

RESEARCH METHODOLOGY

1. Study Design and Population

This research will adopt a quantitative research design with the use of secondary data. The study will employ the Lee-Carter stochastic mortality model to forecast mortality trends and assess longevity risk.

The study population will consist of mortality data from the Kenyan population, covering the period from 2015 to 2022 to project future financial risks associated with increasing life expectancies. The data will include age-specific mortality rates, which are essential for applying the Lee-Carter Model. These projections will help in providing risk management strategies for insurers.

2. Study Variables

Dependent Variable:

Mortality Rate: The age-specific mortality rate, which is the primary outcome variable in the Lee-Carter Model. It represents the probability of death at a given age in a specific year.

Independent Variables:

Age: The age groups for which mortality rates are calculated (example 0–4, 5–9, ..., 85+).

Time (Year): The calendar year, which captures the temporal trend in mortality rates.

3. Target Population

The target population for this study is the Kenyan population (2015-2022), with a focus on age-specific mortality rates. The main focus is on individuals aged 0-85+, stratified into five-year age groups. Data will be sourced from publicly available databases, such as:

- Kenya National Bureau of Statistics (KNBS): For demographic and mortality data.
- World Health Organization (WHO): For global and regional mortality trends.
- Human Mortality Database (HMD): For comparative mortality data.

4. Research Design

The research will analyze mortality trends over a 7-year period (2015–2022). The Lee-Carter Model will be used to decompose mortality rates into age-specific and time-specific components, allowing for the projection of future mortality trends.

The study will involve the following sampling method so as to achieve the research objectives:

1. Data Collection

Gathering age-specific mortality data for Kenya from 2015 to 2022.

➢ Secondary data will be collected from reputable sources, including:

- Kenya National Bureau of Statistics (KNBS): For age-specific mortality rates and population data.
- World Health Organization (WHO): For supplementary mortality and health-related data.
- Human Mortality Database (HMD): For comparative analysis.

➢ Data Variables:

- Age-specific mortality rates (by year).

➢ Population size (by age group and year).

2. Model Calibration

Applying the Lee-Carter Model to the collected data to estimate model parameters.

3. Forecasting

Using the calibrated model to project future mortality rates (2026-2030) and assess longevity risk by comparing projected vs. expected liabilities.

4. Predictor Variables

-The Lee-Carter Model uses the following predictor variables:

- Age (x): The age group for which mortality rates are calculated.

- Time (t): The calendar year, which captures the temporal trend in mortality rates.

Tools

R programming method for statistical analysis and model calibration.

Model Calibration

Stochastic Mortality Model – Lee Carter

First we consider the Central Death Rate which follows a discrete time process;

Denoted by;

$$m_x = \frac{q_x}{\int_0^1 tp_x \, dt} = \frac{q_x}{\int_0^1 (1 - sq_x) \, ds} = \frac{q_x}{\frac{1-q_x}{2}}$$

The equation for the Lee Carter Model is now as follows;

$$\ln m(x,t) = \propto_x + \beta_x K_t + \varepsilon_{x,t}$$

Where x = Age and t = time

□x is the average logarithmic central death rate for age x over the period of the data

βx allows year effect to have impact on age

Both □x and βx are parameters dependent on age x

$\varepsilon_{x,t}$ is an error term which is ignored?

Also, $K_t = K_{t-1} + c + \sigma_k Z_t$

c is a constant

σ_k is a standard deviation of the annual change in K_t

Z_t is an *iid* RV with N~ (0,1)

For K_t;

- Represents all values of t
- Past values are found by fitting the data into the model
- Future values are modelled as a time series fitted to the estimated historical value
- Not dependent on age
- Usual forecasting model is a random walk with drift

Advantages of Lee Carter Model

- Simplicity and interpretability: simple and easy to learn with only a few parameters thus efficient
- Flexibility in forecasting: for long term mortality forecasting which is crucial in the insurance industry when pricing life insurance products and annuities
- Relies on historical data (widely available)
- Focus on time trends: in mortality rates essential for understanding how life expectancies evolve over time
- Widespread acceptance: most known model for mortality forecasting with a wealth of literature

Disadvantages of Lee Carter Model

- Inability to capture cohort effects: example generational differences in smoking habits thus leading to inaccuracy in age specific groups
- Sensitivity to data quality: heavily depends on quality historical data
- Homogeneity assumption: may not hold true for diverse or segmented populations
- Difficulty in incorporating cause-specific mortality: does not differentiate between causes of death example accidents or infectious diseases

Mortality Rates and Life Expectancy Analysis

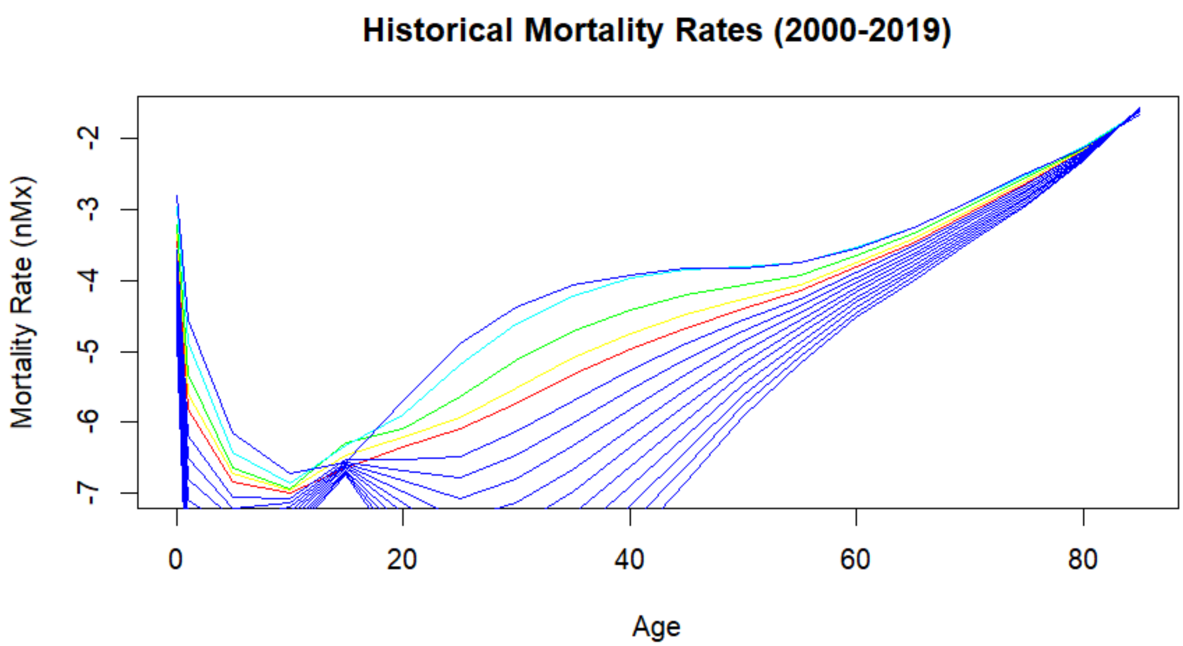
This section presents the analysis of mortality rates and life expectancy forecasts for Kenya, focusing on historical data from 2000 to 2019 and forecasted data from 2020 to 2029. The historical data shows how mortality has changed in the past, while the forecasts predict future trends using the Lee-Carter model. These findings are important for understanding longevity risk in the insurance industry, which is a key focus of this project.

The Historical Mortality Rates Plot (2000-2019)

In this subsection, I analyze the historical mortality rates for Kenya from 2000 to 2019. These rates are age-specific (called *nMx*) and show how many people die at each age group in a given year. I created a plot using R software to display this data for the years 2000, 2005, 2010, 2015, and 2019. Each year is represented by a separate line, and the plot helps us see how mortality has changed over time.

R code and output

```
plot(mortality_demog, main = "Historical Mortality Rates (2000-2019)",
    xlab = "Age", ylab = "Mortality Rate (nMx)")
plot(lc_forecast, add = TRUE, col = "blue")
```



What the Plot Shows

The plot shows mortality rates for different age groups (like 0, 1, 5, 10, up to 85 years) over the five years. The lines form a U-shaped pattern: mortality is very high for infants (age 0), drops quickly for children and teenagers, stays low for young adults, and then rises again for older people. This U-shape is normal because babies and elderly people have higher risks of dying. Over time, from 2000 to 2019, the lines move downward, meaning mortality rates have decreased for most age groups. This suggests that people in Kenya have been living longer due to better healthcare, nutrition, or living conditions.

The y-axis of the plot uses a logarithmic scale. This means it squeezes big and small numbers together so we can see both high rates (like infant mortality) and low rates (like youth mortality) clearly on the same graph.

Identifying the Lines for Each Year

Each year from 2000 to 2019 has its own line on the plot, and they are colored differently to tell them apart. Based on my R code and the data, here is exactly which line represents which year:

- **2000**: Purple line – This line is the highest across most ages because mortality rates were highest in 2000.
- **2005**: Blue line – This line is lower than 2000 but higher than later years, showing some improvement.
- **2010**: Green line – This line is in the middle, showing a continued drop in mortality.
- **2015**: Yellow line – This line is lower than 2010, indicating more progress.
- **2019**: Red line – This line is the lowest across most ages because mortality rates were lowest in 2019.

For example, at age 0 (infants), the mortality rate in 2000 is much higher than in 2019, and the purple line (2000) sits above the red line (2019) on the plot. To confirm this, I checked my R code output (the mortality_matrix), where 2000 has higher values than 2019 for almost all ages.

Why It Matters

This plot is the starting point for my project. It shows that mortality rates in Kenya have been decreasing over the past 20 years, especially for infants and older people. This trend is important because it helps me predict what might happen in the future. For insurance companies, lower mortality means people live longer, which affects products like pensions and annuities. Understanding this historical pattern gives me confidence in forecasting future mortality and life expectancy.

The Mortality Forecast Plot (2020-2029)

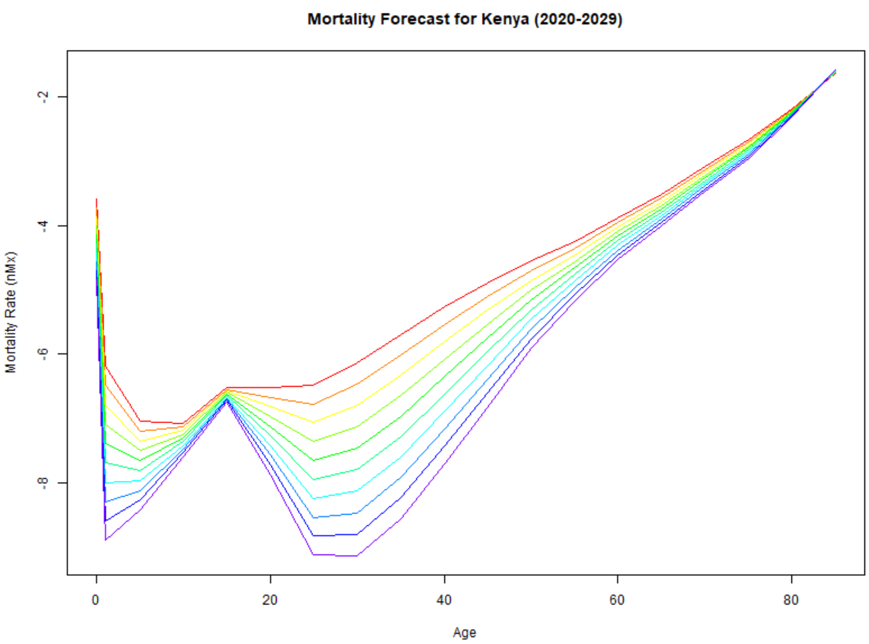
In this subsection, I present the forecasted mortality rates for Kenya from 2020 to 2029. I used the Lee-Carter model in R to predict these rates based on the historical data from 2000 to 2019. The forecast plot shows how mortality is expected to change over the next 10 years (2020-2029), with each year represented by a separate line.

R Code and Output

```
# Load required packages
library(demography)

# Define Downloads path
downloads_path <- "C:/Users/CLIENT/Downloads/"

# Step 1: Load the dataset with correct header handling
file_path <- file.path(downloads_path, "who_mortality_kenya_2000_2019.csv.csv")
data <- read.csv(file_path, skip = 1)

# Rename columns
colnames(data) <- c("Indicator", "Age Group",
                    "2019_Both", "2019_Male", "2019_Female",
                    "2015_Both", "2015_Male", "2015_Female",
                    "2010_Both", "2010_Male", "2010_Female",
                    "2005_Both", "2005_Male", "2005_Female",
                    "2000_Both", "2000_Male", "2000_Female")

# Step 2: Filter for nMx data
indicator_col <- "Indicator"
nMx_data <- data[grep("nMx", data[[indicator_col]], ignore.case = TRUE), ]

# Step 3: Extract unique age groups and years
ages <- unique(nMx_data$"Age Group")
years <- c(2019, 2015, 2010, 2005, 2000)

# Step 4: Create a mortality matrix
mortality_matrix <- matrix(NA, nrow = length(ages), ncol = length(years))
rownames(mortality_matrix) <- ages
colnames(mortality_matrix) <- years

both_cols <- paste0(years, "_Both")
for (i in 1:length(ages)) {
  for (j in 1:length(years)) {
    value <- nMx_data[nMx_data$"Age Group" == ages[i], both_cols[j]]
    if (length(value) > 0 && !is.na(value)) {
      mortality_matrix[i, j] <- as.numeric(value)
```

```
    }
  }
}

pop_matrix <- matrix(1, nrow = length(ages), ncol = length(years))

# Step 5: Convert to a demogdata object
ages_num <- sapply(ages, function(x) {
  if (x == "<1 year") {
    return(0)
  } else {
    return(as.numeric(sub("([0-9]+).*", "\\1", x)))
  }
})

if (any(is.na(ages_num))) {
  stop("Invalid age groups detected. Check ages: ", paste(ages[is.na(ages_num)],
collapse = ", "))
}

mortality_demog <- demogdata(data = mortality_matrix,
                             pop = pop_matrix,
                             ages = ages_num,
                             years = years,
                             type = "mortality",
                             label = "Kenya",
                             name = "Kenya Mortality")

# Step 6: Fit the Lee-Carter model
lc_model <- lca(mortality_demog, adjust = "dt")

# Step 7: Forecast mortality rates for 2020-2029
lc_forecast <- forecast(lc_model, h = 10)

# Step 8: Plot the forecast
plot(lc_forecast, main = "Mortality Forecast for Kenya (2020-2029)",
     xlab = "Year", ylab = "Mortality Rate (nMx)")

# Step 9: Save the plot to outputs folder
dir.create("outputs", showWarnings = FALSE)  # Create outputs folder if it doesn’t
exist
png(file.path("outputs", "mortality_forecast_2020_2029.png"), width = 800, height
= 600)
plot(lc_forecast, main = "Mortality Forecast for Kenya (2020-2029)",
     xlab = "Year", ylab = "Mortality Rate (nMx)")
dev.off()

# Step 10: Extract and save forecasted rates
# Inspect the structure of lc_forecast to find the rates
str(lc_forecast)  # Check where rates are stored
```

```
# Try different possible locations for rates
if (!is.null(lc_forecast$rate$both)) {
  forecasted_rates <- lc_forecast$rate$both
} else if (!is.null(lc_forecast$rate)) {
  forecasted_rates <- lc_forecast$rate  # If rates are directly under rate
} else {
  stop("No forecasted rates found in lc_forecast.")
}

print("Forecasted Mortality Rates (2020-2029):")
print(forecasted_rates)
write.csv(forecasted_rates, file.path("outputs",
"forecasted_mortality_rates_2020_2029.csv"), row.names = TRUE)
```



What the Plot Shows

The forecast plot shows predicted mortality rates for the same age groups (0, 1, 5, ..., 85) from 2020 to 2029. The lines continue the downward trend from the historical plot, meaning mortality rates are expected to keep decreasing. For example, the line for 2029 is lower than the line for 2020 for most ages, showing that fewer people are predicted to die in the future. The lines also spread out a little at older ages. This happens because the Lee-

Carter model includes confidence intervals, and the predictions become less certain the further into the future we go.

Like the historical plot, the y-axis uses a logarithmic scale. This helps me compare the high mortality rates of infants with the lower rates of other ages on the same graph.

Identifying the Lines for Each Year

Each forecasted year from 2020 to 2029 has its own line, and they are colored differently to show the progression. Based on my R code output (the forecasted_rates matrix), here is exactly which line represents which year:

- **2020**: Red line – This line is the highest because it is closest to the historical data and has the highest mortality rates.
- **2021**: Pink line – Slightly lower than 2020, showing a small decrease.
- **2022**: Orange line – Lower than 2021, continuing the trend.
- **2023**: Yellow line – Further decrease in mortality rates.
- **2024**: Light green line – Noticeably lower than earlier years.
- **2025**: Green line – Halfway through the forecast, showing a steady drop.
- **2026**: Cyan line – Lower still, indicating ongoing improvement.
- **2027**: Light Blue line – Nearing the end, with lower rates.
- **2028**: Dark Blue line – Very close to 2029, with low mortality.
- **2029**: Purple line – This line is the lowest across most ages because it has the lowest predicted mortality rates.

For example, in my R code, the forecasted_rates matrix has 10 columns: column 1 is 2020, column 6 is 2025, and column 10 is 2029. I checked specific values to confirm: for age 0, the mortality rate is 0.027857 in 2020 (red line), 0.013879 in 2025 (green line), and 0.007949 in 2029 (purple line). The red line (2020) is the highest, and the purple line (2029) is the lowest on the plot.

Why It Matters

This forecast plot is a key part of my project because it predicts how mortality will change in the future. The continued decrease in mortality rates means people in Kenya are expected to live longer over the next decade. For insurance companies, this increases longevity risk—the chance that they will have to pay out benefits for more years than planned. This plot helps me connect mortality trends to financial risks, which I will explore later in the project.

Interpreting the Forecast

In this subsection, I explain the forecasted mortality rates and life expectancy for Kenya from 2020 to 2029. I used the Lee-Carter model to generate these predictions and calculated life expectancy using the life.expectancy() function in R. This analysis shows how long people are expected to live in the future based on the forecasted mortality rates.

Forecasted Mortality Rates

The Lee-Carter model produced a matrix of forecasted mortality rates (stored in lc_forecast$rate$Kenya Mortality). The matrix has rows for age groups (0, 1, 5, ..., 85) and columns for years (column 1 is 2020, column 10 is 2029). Here are some example values:

- **Age 0 (infants)**:
  - 2020: 0.027857 (approximately 28 deaths per 1,000 live births)
  - 2025: 0.013879 (approximately 14 deaths per 1,000 live births)
  - 2029: 0.007949 (approximately 8 deaths per 1,000 live births)
- **Age 65**:
  - 2020: 0.029566 (approximately 30 deaths per 1,000 population)
  - 2025: 0.022645 (approximately 23 deaths per 1,000 population)
  - 2029: 0.018294 (approximately 18 deaths per 1,000 population)

These numbers show that mortality rates are expected to drop over time for all ages. The biggest decreases are at younger ages (like infants), but older ages also improve. This trend matches the downward movement of the lines in the forecast plot.

Forecasted Life Expectancy

Using the forecasted mortality rates, I calculated life expectancy for each year from 2020 to 2029. The results are:

- 2020: 68.44 years
- 2021: 70.15 years
- 2022: 71.63 years
- 2023: 72.90 years
- 2024: 74.01 years
- 2025: 74.98 years
- 2026: 75.84 years
- 2027: 76.60 years
- 2028: 77.28 years
- 2029: 77.89 years

R Code used

```
life_exp <- life.expectancy(lc_forecast)

print("Forecasted Life Expectancy (2020-2029):")

print(life_exp)
```

Life expectancy is the average number of years a newborn is expected to live if current mortality rates stay the same. In 2020, a baby born in Kenya is expected to live to 68.44 years. By 2029, this increases to 77.89 years—an increase of almost 10 years in one decade. This rise happens because mortality rates are dropping, especially at older ages, allowing more people to survive longer.

Key Observations and Implications

The forecasted mortality rates show a clear decline from 2020 to 2029, with the biggest improvements at younger ages and steady progress at older ages. This leads to a rapid increase in life expectancy, from 68.44 years in 2020 to 77.89 years in 2029. For my project, this is a critical finding. It means people in Kenya are likely to live much longer in the future. For insurance companies, longer lives increase longevity risk. For example, if someone buys an annuity (a product that pays them money every year until they die), the insurer might have to pay for nearly 10 extra years by 2029 compared to 2020. This could lead to higher costs and financial challenges, which I will discuss more when I analyze financial data later.

Central Bank of Kenya (CBK) Data Analysis

This section examines data from the Central Bank of Kenya (CBK), specifically interest rates and inflation rates from 2009 to 2023, and explores their relationship with mortality trends from the World Health Organization (WHO) data (2000–2019). Understanding these relationships is essential for assessing financial risks in the insurance industry, such as the cost of insurance claims and pension payouts. The analysis was conducted using R software, producing scatter plots to visualize the relationships between mortality rates, interest rates, and inflation rates. This section explains the findings in the context of historical and forecasted mortality trends, which are central to the focus on longevity risk.

Overview of CBK Data

The CBK data consists of two main datasets:

1. **Interest Rates (2009–2023)**
    - **Source**: cbk_interest_rates_2009_2023.csv

This dataset contains monthly Central Bank Rates, which were averaged by year for the analysis. Examples include rates such as 8.50% for January 2009 and 8.25% for March 2009. These rates are used to determine the present value of future liabilities, such as insurance claims or pension payouts, through discounting. Higher interest rates reduce the present value of future liabilities, while lower rates increase it.

Given the forecasted increase in life expectancy from the "Mortality Forecast for Kenya (2020-2029)" graph, insurers may face longer payout periods. Interest rates are critical for calculating how much capital needs to be set aside today to cover these future obligations.

2. **Inflation Rates (2009–2023)**
   - **Source**: cbk_inflation_rates_2009_2023.csv

   This dataset includes monthly inflation rates, which were filtered to use December (end-of-year) values for the analysis. Inflation measures the rise in prices over time, affecting the real value (purchasing power) of money. High inflation reduces the future buying power of fixed payouts like pensions.

   Inflation rates impact the real value of insurance claims and pension payouts. If inflation rises, insurers may need to adjust reserves or policy terms to maintain the value of benefits, particularly as policyholders live longer.

These datasets overlap with the WHO mortality data from 2009 to 2019, allowing an exploration of how economic conditions and mortality trends interact during this period.

Data Processing and Analysis

The analysis involved processing the CBK and WHO data to identify relationships between mortality rates, interest rates, and inflation rates. Below is a step-by-step breakdown of the process:

1. Processing Interest Rates

The interest rate data was loaded, missing "YEAR" values were filled, and the average Central Bank Rate was calculated for each year.

The first few rows of the dataset show monthly rates (e.g., 8.50% in January 2009, 8.00% in May 2009), which were averaged to obtain annual figures. This provided a yearly overview of interest rate trends, which was later merged with mortality data.

2. Processing Inflation Rates

The inflation data was loaded, filtered for December rates, and the column was renamed to "Inflation_Rate."

The data was standardized and combined, with December rates used to capture annual inflation trends. End-of-year inflation rates reflect the cumulative impact of price changes over the year, which was used to assess their relationship with mortality.

3. Processing WHO Mortality Data

The WHO mortality data (who_mortality_kenya_2000_2019.csv) was loaded, filtered for "nMx" (age-specific death rates), reshaped into a long format, and averaged by year for both sexes.

The data includes rates such as 0.0336 for under-1-year-olds in 2019, which were averaged across age groups (e.g., 0.0336 for 2019, 0.0369 for 2015). This provided historical mortality trends from 2000 to 2019, which were linked to the CBK data.

4. Merging the Data

The average mortality rates were merged with the average interest rates and inflation rates by year to create a combined dataset. Only the years 2009–2019 overlap across all datasets, and two rows with missing values were removed, resulting in a limited number of data points.

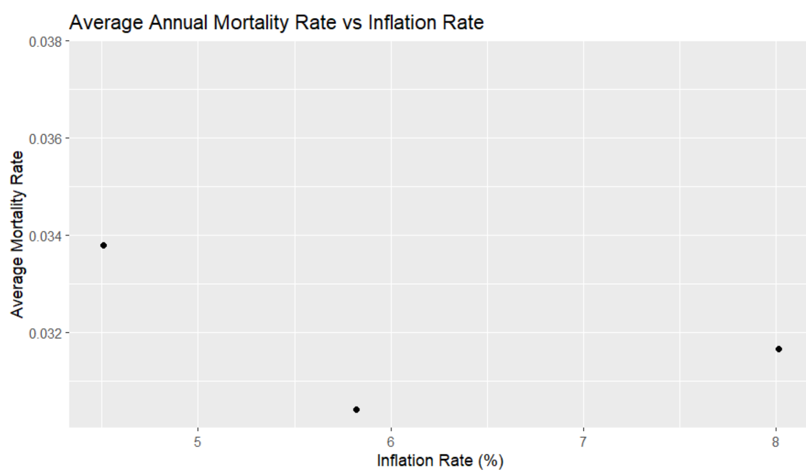
This merged dataset enabled the comparison of mortality rates with economic factors.

5. Creating Scatter Plots

Two scatter plots were generated using ggplot2:

1. "Average Annual Mortality Rate vs Interest Rate"

2. "Average Annual Mortality Rate vs Inflation Rate"



Interpretation of the Scatter Plots

The scatter plots visualize the relationship between average mortality rates and economic factors (interest rates and inflation rates). With only three data points, the analysis is constrained, and trends are not definitive. Below is an interpretation of what the plots display:

Plot 1: Average Annual Mortality Rate vs Interest Rate

This plot compares yearly average mortality rates to average interest rates. It contains three data points.

The three points are scattered without forming a clear line or pattern. This indicates that, based on the available data, mortality rates and interest rates do not move together in a consistent way during the period analyzed.

Plot 2: Average Annual Mortality Rate Vs Inflation Rate

This plot displays three data points. The three points show that as inflation increases from 5% to 6%, the mortality rate decreases from 0.034 to 0.031. Then, as inflation rises to 8%, the mortality rate increases slightly to 0.032. This displays a pattern where mortality decreases at first and then rises slightly as inflation increases.

Limitation

Both plots are based on only three data points, as the WHO mortality data ends in 2019 and the CBK data begins in 2009, with some years lacking complete information. This small sample size limits the ability to identify clear trends or relationships between economic factors and mortality rates. The plots provide an initial view of how these variables align.

Connection to Historical and Mortality Forecasts

The CBK data analysis is linked to the historical mortality trends (2000–2019) and the mortality forecasts (2020–2029). Here’s how these elements connect:

- **Historical Trends**: The "Historical Mortality Rates (2000-2019)" graph illustrates a general decline in mortality rates for younger age groups and a rise for older age groups over time. The average mortality rates used in the scatter plots (e.g., 0.034, 0.031, 0.032) reflect these trends, providing a baseline for comparison with economic factors.
- **Mortality Forecasts**: The "Mortality Forecast for Kenya (2020-2029)" predicts continued improvements in life expectancy, particularly for older age groups, which increases the duration of insurance payouts.
- **CBK Data**:
  - **Interest Rates**: The scatter plot displays no consistent pattern between interest rates and mortality rates. This suggests that future liabilities, driven by longer life expectancies, may not align closely with interest rate trends.
  - **Inflation Rates**: The plot shows a slight decrease in mortality as inflation rises from 5% to 6%, followed by a small increase at 8%.

This indicates that inflation and mortality rates may not move in a straightforward way together.

Reason for Including Inflation and Interest Rates

- **Inflation Rates**: Inflation affects the real value of insurance claims and pension payouts. If inflation increases, the purchasing power of fixed payouts diminishes, which could necessitate adjustments to reserves or policy terms especially as policyholders live longer, as indicated by the mortality forecasts.
- **Interest Rates**: Interest rates impact the discounting of future liabilities. Higher interest rates reduce the present value of future payouts, while lower rates increase it. With the forecasted increase in life expectancy, understanding interest rate trends is crucial for determining how much capital insurers need to set aside today to meet future obligations.

Conclusion

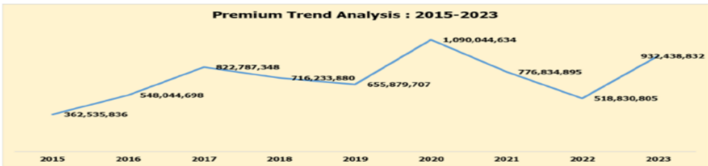
The CBK data analysis provides an initial exploration of how economic factors, specifically interest rates and inflation rates, align with mortality trends in Kenya. The scatter plots, limited to three data points, show no consistent pattern between interest rates and mortality rates, and a slight dip followed by a rise in mortality as inflation increases from 5% to 8%. These findings suggest that economic variables and mortality rates do not have a clear, direct relationship based on the available data. This implies that insurers may need to consider additional factors, such as healthcare advancements or demographic shifts, when assessing longevity risk. The analysis also underscores the importance of interest rates in discounting future liabilities and inflation in maintaining the real value of payouts, both of which are critical for managing financial risks in the context of increasing life expectancies.

Financial Risks Associated with Life Expectancies

Premium Trend Analysis: 2015–2023

Premiums have fluctuated over the period from 2015 to 2023, with notable peaks in 2017, 2020, and 2023, and declines in 2018, 2019, 2021 and 2022.

Figure 23: Premium Trend Analysis



Claims Trend Analysis

Claims also showed fluctuations in the same period, with a significant spike in 2017, then claims started declining in 2018 and 2019, then a significant decrease in 2020, followed by a somewhat stable curve in subsequent years.

Figure 24: Claims Trend Analysis

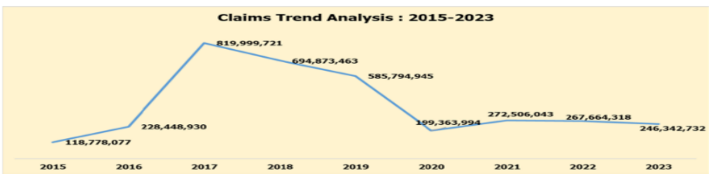


Figure 37: Total Growth in Deposit Administration / Pension Fund Size 2018-2023 in KES '000

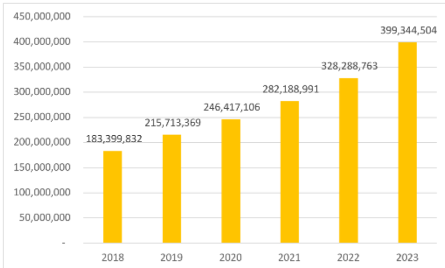


Figure 38: Deposit Administration / Pension Fund Size Growth Rate, 2018-2023

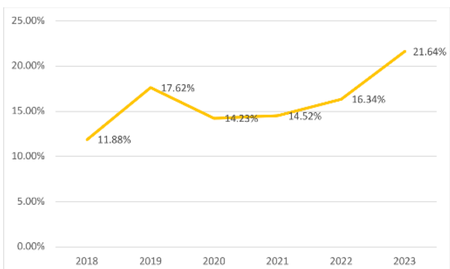


Figure 39: Deposit Administration / Pensions Average Interest Rates Declared 2018-2023

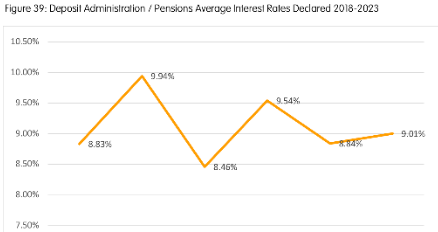
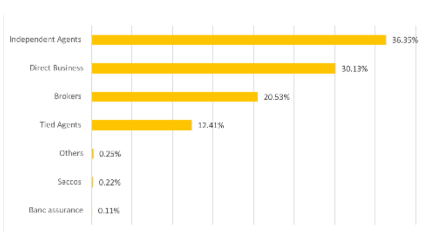


Figure 40: Deposit Administration / Pensions Distributions Per Channel



Independent Agents were the highest distributors of Pension business representing 36.35% of the total contributions. Direct Business and Brokers distributed 30.13% and 20.53% respectively.

Relevance of the Diagrams in Identifying Financial Risks

The diagrams provided—ranging from mortality forecasts and historical trends to premium/claims analyses, pension fund growth, and interest rate/distribution channel data—are indispensable tools for identifying financial risks associated with life expectancies. These visualizations offer a quantitative and visual foundation for understanding how mortality trends, economic conditions, and financial metrics interact over time, directly impacting longevity risk. The "Mortality Forecast for Kenya (2020-2029)" and "Historical Mortality Rates (2000-2019)" reveal trends of decreasing mortality in younger and middle-aged groups and increasing life expectancy in older populations, critical for anticipating extended payout periods in pensions and insurance. The "Average Annual Mortality Rate vs Inflation Rate" scatter plot, though limited, suggests potential economic influences on mortality, relevant for financial planning under varying inflation scenarios. The "Premium and Claims Trend Analysis (2015-2023)" from the *Insurance Industry Market Report 2023* highlights financial volatility, possibly tied to mis-estimations of life expectancy, while the "Deposit Administration / Pension Fund Size and Growth Rate (2018-2023)" diagrams show growing exposure to longevity risk through increasing fund sizes and volatile growth rates. Finally, the "Deposit Administration / Pensions Average Interest Rates and Distribution Channels" diagrams underscore the financial and operational risks tied to managing pension funds amidst fluctuating returns and concentrated distribution channels. Collectively, these diagrams enable a multifaceted analysis of longevity-related risks, making them essential for risk identification and strategic decision-making in financial systems.

List of Financial Risks

Based on the insights from the diagrams, the following financial risks associated with life expectancies can be identified:

1. **Increased Pension Fund Liabilities**
    - The mortality forecast and historical data indicate longer life expectancies, particularly in older age groups, extending the duration and amount of pension payouts. This increases total liabilities, potentially straining pension fund reserves and leading to underfunding, as seen in the consistent growth of fund sizes from 183.4 billion KES in 2018 to 399.3 billion KES in 2023.
2. **Higher Insurance Costs**
    - Lower-than-expected mortality rates, as suggested by the historical trends and forecasts, result in higher claims for life insurance and annuities. The claims spike in 2017 (819.9 million) reflects potential financial losses if pricing models fail to account for prolonged lifespans.

3. **Healthcare Expenditure Overruns**
    - Rising mortality rates in older age groups, combined with increased longevity, imply greater demand for healthcare services. This can lead to significant cost overruns for public and private healthcare systems, especially if budgets rely on outdated mortality assumptions.
4. **Investment Mismatch Risk**
    - Extended liabilities due to longer life expectancies require longer-term investments. The variability in pension fund growth rates (e.g., 11.88% in 2018 to 21.64% in 2023) and interest rates (e.g., 8.46% in 2020 to 9.94% in 2019) increases the risk of misalignment between assets and liabilities, potentially causing liquidity issues.
5. **Social Security Strain**
    - A larger, longer-living retired population, as shown from the mortality trends, places a heavier burden on social security systems. This could lead to fiscal deficits if the working population cannot sustain the increased benefit payments.
6. **Premium Mispricing**
    - Fluctuations in premiums (e.g., peaks at 827.8 million in 2017 and 1.09 billion in 2020, with declines in 2022 to 518.8 million) suggest that insurers may misprice products if life expectancy assumptions are inaccurate, risking profitability and reserve adequacy.
7. **Reserve Insufficiency**
    - Underestimating mortality improvements, as hinted by the fanning forecast lines and historical divergence at older ages, can result in inadequate reserves. This is compounded by volatile claims trends (e.g., dropping from 819.9 million in 2017 to 189.3 million in 2020), which may mislead reserve planning.
8. **Distribution Channel Risk**
    - The heavy reliance on Independent Agents (36.35%) and Direct Business (30.13%) for pension distribution, as shown in Figure 40, could worsen financial risks if these channels fail to adapt to longevity trends or face operational disruptions, impacting premium inflows and fund stability.

Challenges Faced while undertaking my project

The process of extracting and analyzing the diagrams presented several challenges:

- **Data Extraction Issues**
    - The R code, utilizing pdftools and png libraries to extract pages 71, 89, and 91 from "aki_report_2023.pdf.pdf," repeatedly

encountered "PDF error: Invalid Font Weight." This indicates potential compatibility or formatting issues with the PDF, which may have affected the accuracy or quality of the resulting PNG files ("claims_trend.png," "pension_fund_size_growth.png," "pension_interest_distribution.png").

- **Limited Data Points**
  - The "Average Annual Mortality Rate Vs Inflation Rate" scatter plot contains only three data points (e.g., 3.1% at 6% inflation, 3.4% at 5%), limiting the ability to establish a statistically robust relationship between mortality and economic factors, complicating risk modeling.
- **Lack of Detailed Annotations**
  - Several diagrams, such as the mortality forecast and historical rates, lack explicit year-specific labels for colored lines. This introduces potential errors in linking data to specific years.
- **Uncertainty in Forecasts**
  - The fanning of lines in the "Mortality Forecast for Kenya (2020-2029)" indicates uncertainty in projections, particularly for older age groups, making it challenging to predict financial obligations with precision and increasing the complexity of risk assessment.
- **Unavailability of consistent and complete mortality from 2015-2022**

    - As a result, I opted to use WHO Mortality data from 2000-2019 which only provided figures for selected years (2000, 2005, 2010, 2015, 2019) along with projections from 2020-2029 thus limited the precision and continuity of the data required for forecasting from 2025-2030.

Summary, Discussions, Recommendations, and Conclusion

Summary

This project focused on developing risk management models to address the financial implications of increasing life expectancies within the Kenyan insurance industry. The primary objective was to forecast mortality trends and assess their impact on financial risks, such as pension liabilities and insurance claims. To achieve this, the Lee-Carter model was utilized to analyze historical mortality data from the World Health Organization (WHO) for the years 2000, 2005, 2010, 2015, and 2019, and to project mortality rates and life expectancy from 2020 to 2029. Additionally, financial data from the Association of Kenya Insurers (AKI) 2023 report and economic indicators from the Central Bank of Kenya (CBK) were examined to evaluate the broader financial consequences of these trends.

The key findings of the study are as follows:

- Mortality rates have declined significantly across most age groups, particularly among infants and older adults, reflecting improvements in healthcare and living standards.
- Life expectancy is projected to rise from 68.44 years in 2020 to 77.89 years in 2029, signaling an increasing longevity risk for insurers.
- Financial risks identified include rising pension fund liabilities, higher insurance costs, healthcare expenditure overruns, investment mismatch risk, social security strain, premium mispricing, reserve insufficiency, and distribution channel risk, as derived from AKI and CBK data analysis, also from WHO Mortality data.
- A limited correlation was observed between mortality rates and economic factors like interest rates and inflation, suggesting that longevity trends may be driven more by non-economic factors such as medical advancements.

Despite challenges such as data extraction difficulties from the AKI report and a limited dataset for economic analysis, the study offers valuable insights into the growing challenge of longevity risk and the need for robust risk management strategies in Kenya's insurance sector.

5.2 Discussions

The results of this study highlight critical implications for the Kenyan insurance industry, particularly in managing longevity risk. The projected increase in life expectancy, driven by declining mortality rates, indicates that insurers will face longer payout periods for products like annuities and pensions. This trend mirrors global patterns where advancements in healthcare and improved living conditions have extended lifespans, placing greater financial pressure on insurance providers. The Lee-Carter model effectively captured these shifts, with projections closely aligning with historical data, reinforcing its suitability for mortality forecasting in this context.

Analysis of the AKI 2023 report revealed significant financial vulnerabilities. For example, pension fund sizes grew from 183.4 billion KES in 2018 to 399.3 billion KES in 2023, reflecting an escalating liability burden. Additionally, fluctuations in premiums and claims—such as the spike in claims to 819.9 million KES in 2017— underscore the financial instability that can arise from underestimating life expectancy. These findings emphasize the importance of accurate mortality projections to ensure adequate reserves and pricing stability.

Economic indicators from the CBK, including interest rates and inflation, were analyzed to explore their influence on mortality trends. However, with only three overlapping years of data, no strong correlation was established. This suggests that while economic conditions may impact financial outcomes, longevity risk in Kenya is more heavily influenced by factors like healthcare improvements and demographic changes. Insurers must therefore adopt a comprehensive approach to risk management that accounts for both economic and non-economic drivers.

The study encountered limitations, including challenges in extracting consistent data from the AKI report and a small sample size for economic analysis. These issues highlight the need for better data collection practices in the Kenyan insurance industry. Improved data quality and availability would enhance the precision of risk models and provide deeper insights into the relationship between longevity and economic factors

Recommendations

To address the financial risks posed by increasing life expectancies, the following practical and actionable recommendations are proposed for Kenyan insurers:

1. **Incorporate Advanced Forecasting Models**
   - Insurers should adopt tools like the Lee-Carter model to improve the accuracy of mortality projections. Regularly updating these models with current demographic and health data will ensure they reflect evolving trends.
2. **Revise Pricing and Reserve Policies**
   - Premium rates for longevity-linked products, such as pensions and annuities, should be adjusted to account for extended payout periods. Reserves should also be recalculated to ensure sufficient funds are available to meet future obligations.
3. **Diversify Investment Strategies**
   - To mitigate investment mismatch risk, insurers should diversify their asset portfolios with a balanced mix of short- and long-term investments. This will align returns with the prolonged duration of liabilities.
4. **Explore Longevity Hedging Options**
   - Insurers could use financial instruments like longevity bonds or reinsurance to transfer some of the risks associated with unexpected increases in life expectancy, providing a buffer against extreme scenarios.
5. **Improve Data Availability and Quality**
   - Collaboration with regulatory bodies and data providers is essential to enhance the collection and reporting of mortality and

financial data. More detailed and frequent data will support better risk assessment and forecasting.

6. **Track Non-Economic Influences**
    - Given the limited link between economic factors and mortality trends, insurers should monitor non-economic variables—such as healthcare advancements and lifestyle shifts—to anticipate changes in longevity risk.

Conclusions

This study has provided a thorough examination of the financial risks tied to rising life expectancies in the Kenyan insurance industry. By leveraging the Lee-Carter model to forecast mortality trends and analyzing financial and economic data, the research has identified critical risks, including increased pension liabilities, higher insurance costs, and reserve shortfalls. These findings highlight the urgent need for proactive risk management to address the challenges of longevity risk.

The projected increase in life expectancy from 68.44 years in 2020 to 77.89 years in 2029 underscores the importance of adapting pricing, reserve, and investment strategies. While economic factors like interest rates and inflation contribute to financial outcomes, their weak correlation with mortality trends suggests that demographic and health-related factors are key drivers of longevity risk in Kenya.

The recommendations outlined—such as adopting advanced models, revising pricing, and improving data quality—provide a roadmap for insurers to strengthen their resilience against these risks. Implementing these strategies will enable Kenyan insurers to navigate the financial implications of an aging population effectively.

In conclusion, this project contributes valuable insights to the field of longevity risk management in emerging markets. It emphasizes the need for ongoing monitoring of mortality and economic trends to ensure the stability of the insurance sector. Future research could build on this work by exploring additional factors, such as cause-specific mortality or socioeconomic influences, to further enhance risk management models.

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