



UNIVERSITY OF
LIVERPOOL

MATH391 MATHS SUMMER INDUSTRIAL RESEARCH PROJECT

Constructing Ghana Mortality Table via Negative Binomial Regression

Authors: Jingxuan Xu, Lina Peng, Yujia Li, Tianze Shang

Supervisor: Dr. Emmanuel Coffie

PhD student: Cedric Koffi

November 25, 2022

Abstract

One of the models that commonly used in the fitting and forecasting of demographic data is the Negative Binomial model, which is a GLM (Generalized Linear Model) based on the negative binomial regression and count data. There is no dataset and constructed tables for Ghana in recent years. Hence this thesis seeks to fit the raw dataset of an insurance company during 2018-2020 into the Negative Binomial Regression Model. The better of the offset and non-offset models was selected by likelihood ratio test and the best-fit model was selected by comparing AIC and BIC. Based on this, we forecast the mortality rates between 2021-2025, and therefore construct the mortality table of Ghana for this time period.

Contents

1	Introduction	3
2	Processing Data	4
2.1	Description of Raw Data	4
2.2	Calculation of Death Count	5
2.3	Calculation of Exposure	7
2.4	Estimation of Observed Mortality Rate	10
2.5	Insufficient Data and Solutions	12
3	Modeling Methodology	13
3.1	Mathematical Rationale of Negative Binomial Regression model	13
3.1.1	PMF of Response Distribution	13
3.1.2	Mean and Variance, Overdispersion	13
3.1.3	Basic Concept of Negative Binomial Model	14
3.1.4	Estimating Parameters: Maximum Likelihood Estimation	15
3.1.5	Offset	15
3.2	Construction of Model	16
3.2.1	Offset and Non-offset Models	16
3.2.2	Likelihood Ratio Test	17
3.2.3	AIC & BIC Criteria	18
3.2.4	Modeling of Death Count	19
3.2.5	Modeling of Exposure	22
3.3	Fitted Mortality Rate	25
4	Model Assessment	27
4.1	Residual Analysis	27
4.1.1	Deviance Residual	27
4.1.2	Anscombe Residual	29
4.1.3	Simulated Residual: DHARMA Package	31
4.2	Upper Tail Assessment	35
4.3	Forecasting and assessment	36
5	Construction of Mortality Table	39
5.1	Definition of Parameters	39
5.2	Result Table	41
6	Conclusion	57
7	Acknowledgments	60
A	Appendix: R code	61

1 Introduction

Mortality not only affects the population of a country or region but also has a non-negligible impact on the structure of the population and is an integral part of the study of demography and population economics. A mortality table, also known as an actuarial table or life table, generally shows the death rates of some specific demographics, classified by variables ranging from sexes, age groups, year intervals, etc[1]. Parameters which provide more information such as life expectancy, are also embraced in the table. Generalized linear models are frequently used to process these data [11].

Linear regression models are often used to calculate variables such as mortality data for how many times something happens. However, this type of data is considered to be the amount of data that contains the offset variable. Most of the previous studies have applied the Lee-Carter model and seldom mentioned the Negative binomial model in forecasting mortality[2]. However, some did apply a negative binomial model during mortality forecasting [3, 5]. A comparison has been made between Poisson or negative binomial regression and Lee-Carter models [3], while the negative binomial model is considered to be more appropriate than other count models in the sense that its dependent variable is a count data [12]. It is assumed by [10] that the dependent variable is overdispersed and does not have an excessive number of zeros. Variables in the model also have an impact on the goodness of fit. For this problem,[7] introduced the likelihood ratio test in R, which compares the goodness of the fitness between two nested regression models based on the ratio of their likelihoods in statistics.

Most of the mortality tables over the world are constructed and enhanced by HMD (Human Mortality Database)[13]. There is a large data suggesting that the mortality rate peaks at age 0, then decreases slowly and bottoms at age 10. After that, the death rate will climb with fluctuation before age 60 and surges since then. Therefore, the model had been modified based on this common rule. First, our group applied the likelihood ratio test to the offset and non-offset models aiming to select the better. Then the tools of AIC and BIC were used on a series of models to provide the best fit.

For the evaluation of the models, residual diagnostics for hierarchical (multi-level/mixed) regression models is explained in detail [8]. The software will always produce values for the null deviance and residual deviance of the general linear model. [14] gives an example which is using student status, bank balance, and income to build a logistic regression model that predicts the probability given individual defaults. It observed that the Null deviance is 2920.6 with df = 9999, and Residual deviance is 1571,5 with df = 9996. After that using the Chi-Square to P-Value Calculator to find that a X^2 value of 1331.6 with 3 degrees of freedom has a p-value of 0.000000. The model is highly useful for predicting because this p-value is much less than 0.5.

Mortality tables play an essential role in the fields of the decision of insurance policies, construction of pension or annuity systems and liability management. It is also an important database for life insurance actuarial calculations which involves the pricing of life products and reserve retention. [4] introduces GLMs and addresses problems specific to insurance data. A well-fitted and forecasted mortality table would efficaciously help insurance companies lucrative, and even improve the life and well-being of people.

2 Processing Data

2.1 Description of Raw Data

The raw data was provided by a Ghana insurance company, containing over 300,000 rows of data. It includes two parts of data:

- The basic information about individual insurance policies.
- A tremendous matrix of exposure to risk.

The basic information provided by the raw data set for the individual insurance policies part is shown as the table below (for the confidential reason, the example data in this figure is simulated).

Variable	Definition	Example
Policy_No	The serial number of the insurance policy	ABC00000000
Product	The product related to the policy, Whole Life Insurance/Term Insurance	Term Insurance
DOB	The date of birth of the insurant	1900/1/1
Sex	The sex of the insurant	Male
PolicyStatus	Defined as Inforce/Death/Surrender/Matured/Lapsed/Cancelled/Other	Inforce
DateOfInception	The date when starting the policy officially	2018/1/1
DateOfExit	The date when ending the policy (if not ended yet, then it is NA)	2019/1/1
Group/Individual	The insurant of the policy (group or individual policy)	Individual
Medical_Underwriting?	A binary variable defining whether the insurant has medical underwriting	No
Smoker	A binary variable defining whether the insurant is a smoker	No
CauseOfDeath	Defined as categorical variables of several cause of death or NA	Cancer
DateOfDeath	Defined as the date of death of the insurant or NA if not dead yet	2019/1/1
ANB at entry	The "Age nearest birthday" when entering the policy	30
ANB at death	The "Age nearest birthday" when dead or NA	NA
Duration_Inforce	The exposure to risk of this insurant's policy	2.66

Table 1: The variables in the raw data and their definitions and examples

It included not only the date of the insurant death but also, for instance, their death reason, duration in force and age when taking the policy. All of these were stored in a tremendous excel file. However, the raw data was not suitable for processing since there were too many invalid items which may affect the outcome of the modelling. For example, the variable "Smoker" is somehow assigned as "No". It is not reasonable and it is useless to conclude this in our modelling process. Moreover, the massive amount of data caused much trouble to deal with. Firstly, the file is so big that standard software like Microsoft Excel and Numbers could not open it. Therefore, other programming software was adapted to handle the situation. Finally, the programme R opened the dataset, and all the useless columns and rows were deleted from it. Until then, the procedure of processing data begins.

The other part of the raw data is a gigantic matrix which represents the exposure to risk of policies for separated ages. Denote the number of insurance policies contained in this raw data is m , and the matrix contains the exposure to risk from age 20 to 73. Therefore, the matrix is denoted as:

$$A = \begin{pmatrix} a_{0,20} & a_{0,21} & \cdots & a_{0,73} \\ a_{1,20} & a_{1,21} & \cdots & a_{1,73} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,20} & a_{m,21} & \cdots & a_{m,73} \end{pmatrix}$$

where

$$a_{0,i} = \sum_{j=1}^m a_{j,i}$$

represents the total exposure to risk of this age group and the other components, $a_{i,j}$, represents the exposure to risk of the i insurant at age j .

However, some policies started before 2018, and the exposure to risk is also counted into the whole matrix. Our study time expansion is from 2018 to 2020, thus this matrix cannot be directly used for the exposure variable in the model. Therefore, this part of the raw data is not in our consideration. The calculation of exposure is done afterwards.

2.2 Calculation of Death Count

After obtaining the available dataset, since the software, Microsoft Excel is easy to operate with time data, the one was chosen to be the main instrument for processing the data. The death frequency was the first to be counted. During the procedure, the function in excel “**COUNTIF**” was found to be the most efficient way to calculate the death number. The principle of our calculation is (take the 2018 death count as example):

1. Select the sex of the insurants that to be considered (Male or Female).
2. Select the insurants that is in some specific age group by calculating 2018 – the date of birth.
3. Count the number of people whose policy status is stated as ”Death”. Every death data is counted as 1.
4. Add all together and form the integrated table of observed death count table.

So, the insureds who were dead within the policy period were filtered out and counted year by year. Then the form which contains the death count of different ages in different years is constructed. The part of the integrated data set (Age 34 - 66) is illustrated as figure 1 below. The chart was used to model the curve of death number d_x in the following steps.

2018			2019			2020			
Female		Male	Female		Male	Female		Male	
Age	Frequency	Age	Age	Frequency	Age	Age	Frequency	Age	
34	1	34	1	34	1	34	2	34	1
35	1	35	3	35	0	35	2	35	0
36	0	36	0	36	1	36	4	36	5
37	1	37	1	37	1	37	0	37	2
38	2	38	1	38	0	38	1	38	2
39	2	39	5	39	2	39	0	39	2
40	0	40	2	40	2	40	0	40	1
41	1	41	2	41	2	41	0	41	2
42	0	42	3	42	2	42	3	42	1
43	0	43	2	43	3	43	2	43	1
44	0	44	1	44	1	44	2	44	4
45	2	45	0	45	4	45	5	45	7
46	3	46	0	46	1	46	4	46	0
47	2	47	4	47	3	47	1	47	1
48	1	48	4	48	4	48	2	48	1
49	2	49	4	49	2	49	4	49	3
50	2	50	7	50	5	50	2	50	2
51	1	51	3	51	6	51	2	51	6
52	3	52	3	52	4	52	2	52	7
53	5	53	6	53	9	53	3	53	7
54	4	54	7	54	6	54	6	54	2
55	7	55	6	55	6	55	6	55	9
56	8	56	8	56	11	56	9	56	13
57	3	57	5	57	9	57	5	57	8
58	10	58	8	58	10	58	6	58	14
59	5	59	4	59	14	59	14	59	8
60	10	60	16	60	10	60	7	60	8
61	9	61	11	61	16	61	13	61	9
62	9	62	7	62	19	62	18	62	17
63	5	63	13	63	11	63	12	63	22
64	15	64	21	64	17	64	10	64	16
65	4	65	12	65	15	65	14	65	21
66	12	66	16	66	13	66	25	66	10

Figure 1: Observed death count data (Age 34-66)

The observed data set ranges from 2018 to 2020. To see clearly the pattern of the observed death count pattern, diagrammatic presentations of this data set is illustrated below.

Observed number of female deaths (2018-2020)

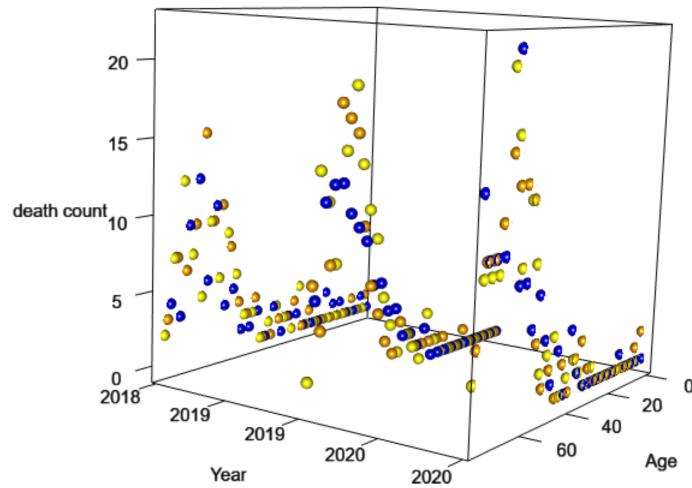


Figure 2: Observed Ghana female death counts from 2018 to 2020

Observed number of male deaths (2018-2020)

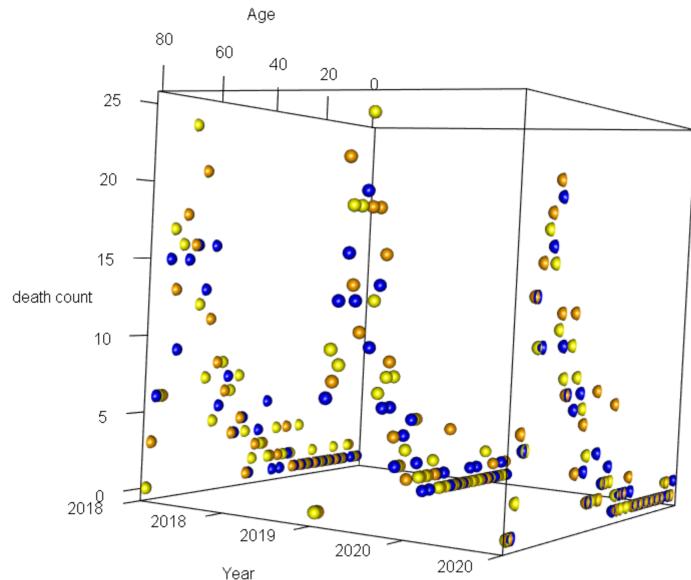


Figure 3: Observed Ghana male death counts from 2018 to 2020

Observed number of total deaths (2018-2020)

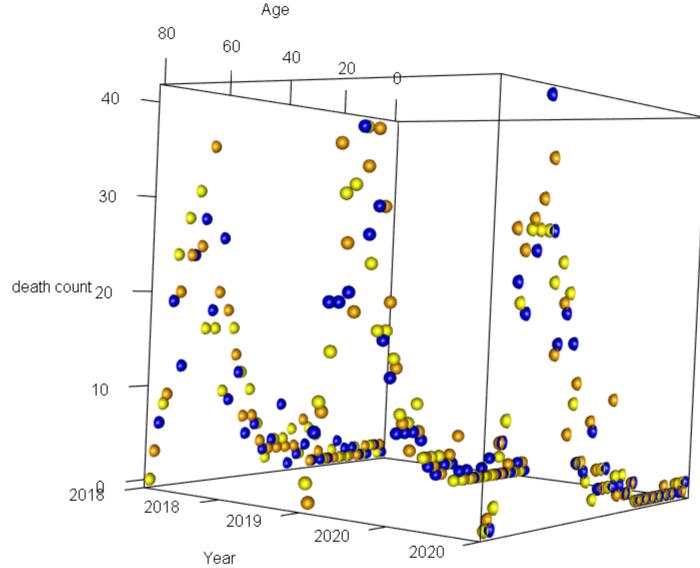


Figure 4: Observed Ghana total death counts from 2018 to 2020

Figure 25, 12 and 13 displayed above depict three-dimensional plots of observed number of death in Ghana from 2018 to 2020, for male, female and total data set, respectively. The death counts of the Ghana people against their ages are observed to be highest among the 60's and 70's age groups but decline steadily; recording minimal counts for 80's age groups. The maximum counts are recorded in 2020 and for age about 70 and the minimum counts are zeros due to the lack of data. We cannot conclude that the death rate declines from 70's to 80's steadily since the exposure to risk is different for every age group.

2.3 Calculation of Exposure

The most significant work for us to handle was the calculation of the exposure. It was a concept that represents the length of the policyholder exposed to the risk of death. However, there are lots of rules to calculate it. Below are calculation regulations provided by [1].

- Only consider Inception and Exit:
 - If Date Of Inception < 1/1/20XX and Date Of Exit > 31/12/20XX, set exposure as 1.



Figure 5: Exposure Calculation Discussion 1

- Only consider Inception and Exit: Otherwise, set Exposure = $a/365$

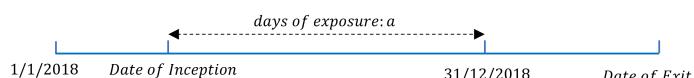
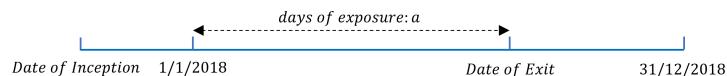




Figure 6: Exposure Calculation Discussion 2

- Add death into consideration:

If the individual died between 2018, overlap the exposure as 1.



Figure 7: Exposure Calculation Discussion 3

As we can see from the figure above, the calculation of the exposure is complicated and requires many efforts and techniques to finish. We still chose Microsoft Excel to complete the work. The data was classified into different categories, and the corresponding techniques were applied to those data to calculate the exposure. After a step explained done above, the next step will overlap part of the results calculated before. Finally, we gained the total exposure of each year respectively.

The 3D plot of the observed exposure data set is shown as below:

Observed Exposure of female (2018-2020)

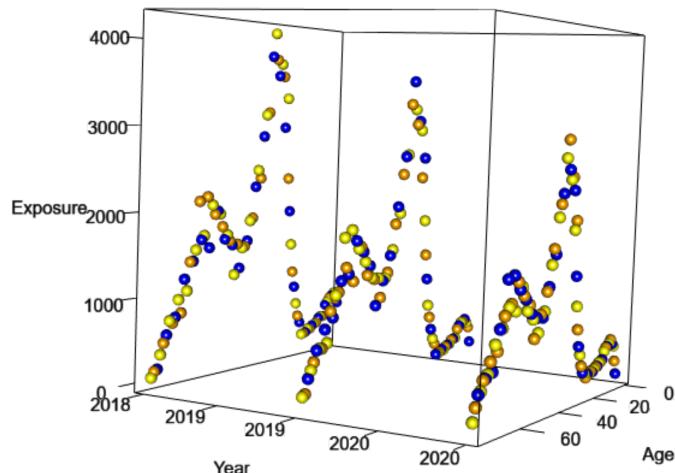


Figure 8: Observed Ghana female exposure from 2018 to 2020

Observed Exposure of male (2018-2020)

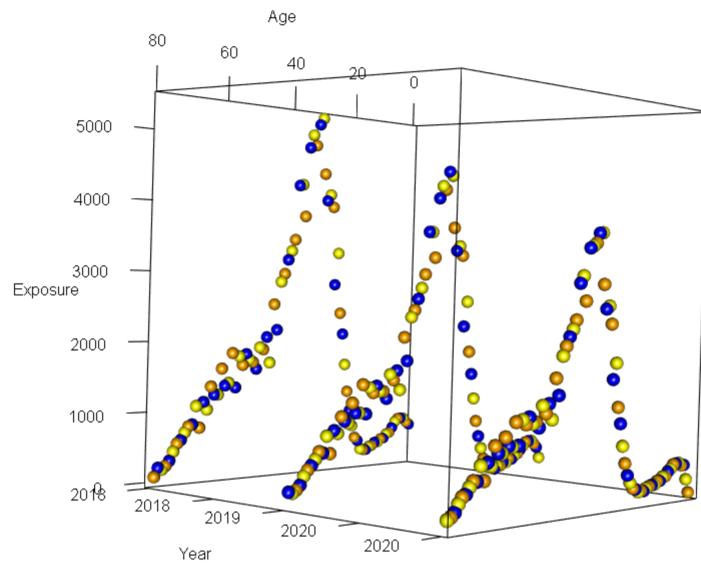


Figure 9: Observed Ghana male exposure from 2018 to 2020

Observed Exposure of total (2018-2020)

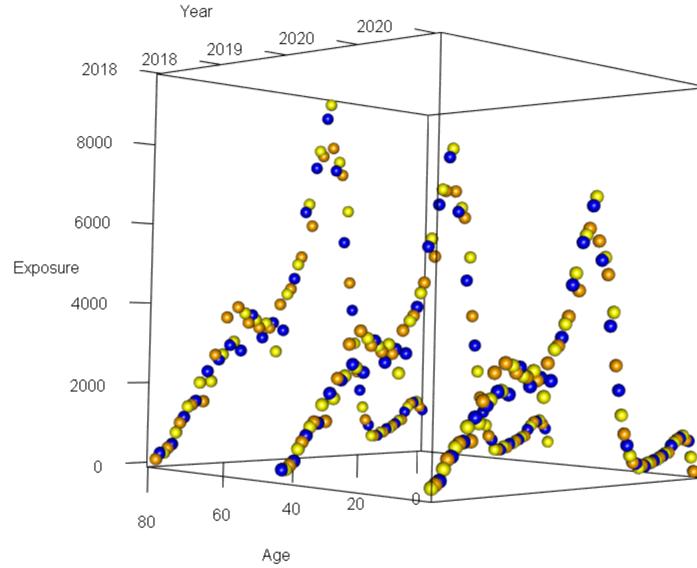


Figure 10: Observed Ghana total exposure from 2018 to 2020

It can be concluded that the exposure for the three data sets stay marginally stagnant at first from 0's to 10's, then going straightly up from 10's to 30's. Afterwards, it declines consistently, though experiencing a mild halt approximately around age 60. The maximum exposure is achieve in 2020 and age about 30, about 9000.

2.4 Estimation of Observed Mortality Rate

After the calculation of all these necessary variables we need to start modelling process, we can actually calculate the observed mortality rate by the formula:

$$\text{Observed Mortality Rate} = \frac{\text{Observed Death Count}}{\text{Observed Exposure}}$$

This data can be used afterwards to assess the goodness of fit by plotting the observed mortality rate and the modeled together to see the consistency.

Here we note that we have many 0s at the lower tail and the upper tail of the observed death count, i.e., at younger age between 0's to approximately 20's and the elder age group between 70's to 80's, leading to the same 0 derived in the observed mortality rate. No zero mortality rate can be applied to the reality. Thus this may affect the accuracy and the goodness of fit of the model. This issue will be addressed later.

We choose to plot the log mortality rate instead of the calculated real mortality rate because:

- To see clearly the pattern of the observed mortality rate since numerically the mortality rate is small.
- To analyse the possible approximate linear pattern since the Negative Binomial Model belongs to the exponential family.

Since $\log 0$ does not exist, we plot $\log(\text{Observed Mortality Rate} + 0.01)$ versus Ages and Years. This applies since it will not change the general pattern of the plot.

Below are 3-dimension graphs for the observed log mortality rate versus ages and years, calculated by the formula above:

Observed Mortality Rate of female (2018-2020)

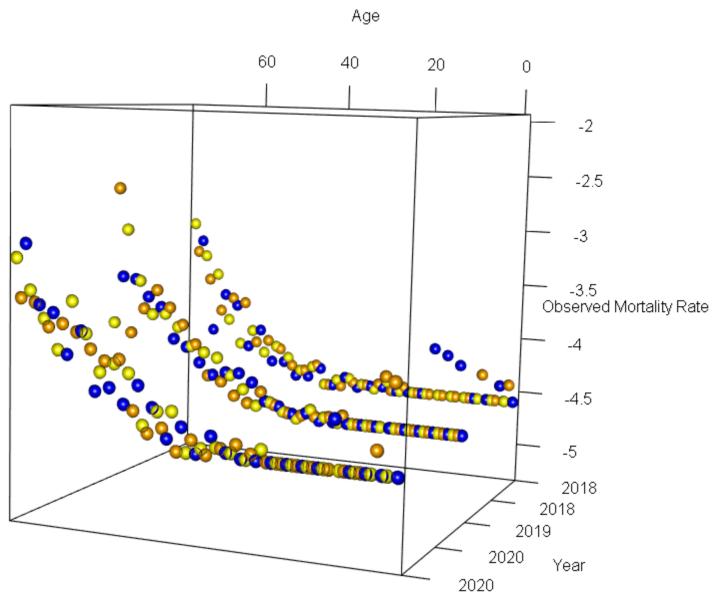


Figure 11: Observed Ghana female mortality rate from 2018 to 2020

Observed Mortality Rate of male (2018-2020)

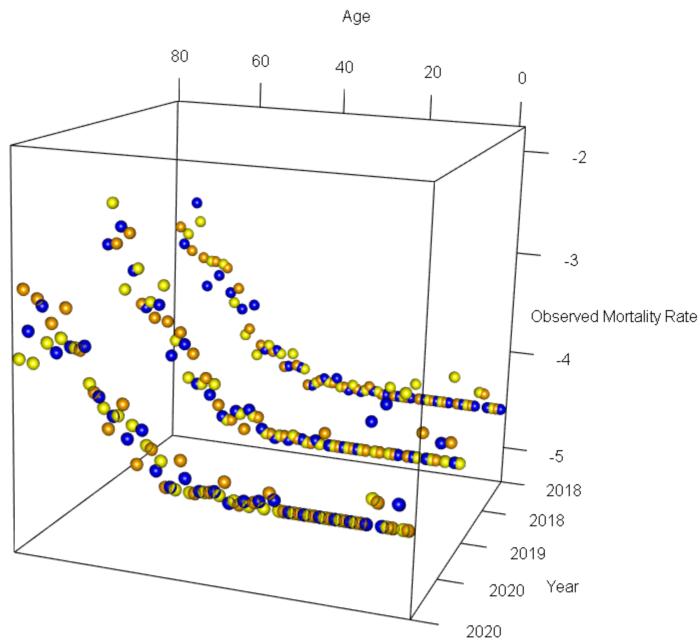


Figure 12: Observed Ghana male mortality rate from 2018 to 2020

Observed Mortality Rate of total (2018-2020)

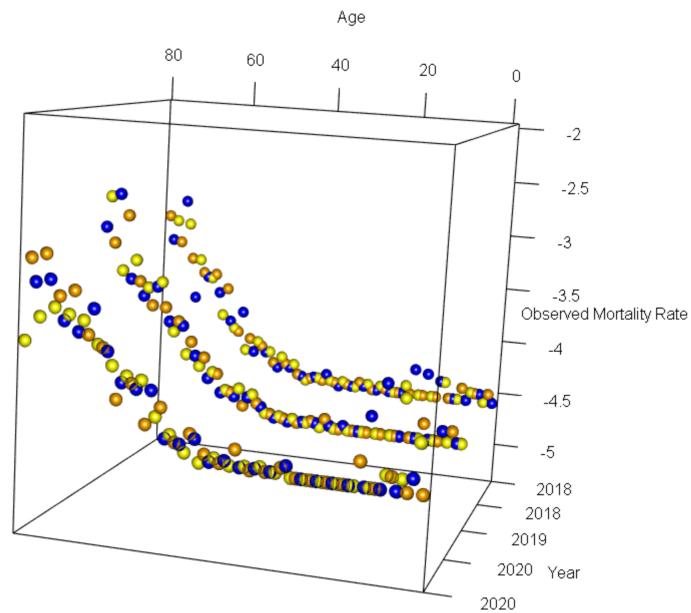


Figure 13: Observed Ghana total mortality rate from 2018 to 2020

The observed log mortality rate stay marginally stagnant with almost no fluctuation at the beginning since there are many 0's in the data set of the observed death count. With the age increasing, the log mortality rate starts to follow an approximately linear pattern, meaning that the real mortality rate starts to follow an approximately exponential pattern. This pattern continues with no discrepancy till the end of the age group we specified.

2.5 Insufficient Data and Solutions

After the data was shown to us, the problem of insufficient data occurred. Since the original data set was so small, only 2000 deaths or so. There are many age periods like age 0-16 and above 76 are very lack of sufficient figures. Considering the data was from an insurance company, the children and elders may not be accepted to be clients, and right and properly not to exist in the dataset.

Clearly from the graphs illustrated in section 2.2 and 2.3, we can see that there are some cases where the death count and the exposure are both zero at age 75-80, i.e., the upper tails of the raw data set, resulting in that the observed mortality rate still cannot be calculated even if we add 0.01 to the mortality rate since we are dividing zero if the exposure is equal to 0. These points are missing in the observed mortality rate plot above. Adding these missing points into consideration as 0 or infinitesimal, the observed mortality rate declines at the end of the age group, which is not consistent with the reality that the death rate increases with age at these local tails. It is proved during the modelling process which will be mentioned later. Considering the deficiencies of both death count and exposure may lead to vast deviation of the final model, we delete the data which the exposure is less than 100 (3 standard deviations below the mean of exposure) at the upper tail to ensure the accuracy.

3 Modeling Methodology

3.1 Mathematical Rationale of Negative Binomial Regression model

After processing the raw data and calculating all the observed values needed, we can step into the modeling part. In this thesis we concentrate on the Negative Binomial Regression model. Described in the subsections below are some necessary concepts for this model.

3.1.1 PMF of Response Distribution

The traditional meaning and derivation of Negative Binomial Distribution is to count m successes among total n trials of a repeated Bernoulli experiment. With this definition the **PMF of Negative Binomial Distribution** can be written as:

$$f(n) = \binom{n-1}{m-1} p^m (1-p)^{n-m}, \quad n = m, m+1, m+2, \dots \quad (1)$$

where p is the probability of success. We can also write this in another way by substituting $n = m + y$ in (1), where y is the total amount of failures.

$$f(y) = \binom{m+y-1}{m-1} p^m (1-p)^y, \quad y = 0, 1, 2, \dots \quad (2)$$

Expand the combination in (2):

$$\begin{aligned} f(y) &= \frac{(m+y-1)!}{(m-1)![m+y-1-(m-1)]!} p^m (1-p)^y \\ &= \frac{(m+y-1)!}{(m-1)!y!} p^m (1-p)^y \end{aligned}$$

Note that for positive integer numbers k , the Gamma function $\Gamma(k) = (k-1)!$. Therefore, the PMF of negative binomial regression can be restated as:

$$f(y) = \frac{\Gamma(m+y)!}{\Gamma(m)y!} p^m (1-p)^y, \quad y = 0, 1, 2, \dots \quad (3)$$

Now, we do some parametrization for the convenience of expressing the mean and variance. We substitute:

$$\mu = \frac{m(1-p)}{p}, \quad \kappa = \frac{1}{m}$$

Substitute into (3) we reach the final expression for PMF:

$$y \sim NB(\mu, \kappa), \quad f(y) = \frac{\Gamma(y+\frac{1}{\kappa})}{y!\Gamma(\frac{1}{\kappa})} \left(\frac{1}{1+\kappa\mu} \right)^{\frac{1}{\kappa}} \left(\frac{\kappa\mu}{1+\kappa\mu} \right)^y, \quad y = 0, 1, 2, \dots \quad (4)$$

3.1.2 Mean and Variance, Overdispersion

The mean and variance of negative binomial distribution can be derived from the Probability Mass Function illustrated above. As a published result [4],

$$\mathbb{E}[y] = \mu, \quad \text{VAR}[y] = \mu + \kappa\mu^2$$

It is clear that, the two parameters in the negative binomial distribution, i.e., μ and κ , represents **the mean of the distribution** and the **scale of quadratic dispersion of variance from the mean**, respectively.

Below are some examples of histograms of negative binomial distribution. The parameter μ controls the mean of the distribution strictly independent of κ , and when κ is big, the histogram is strongly right-skewed and possessing a greater variance. In fact, when $\kappa \rightarrow 0$, $NB(\mu, \kappa) \rightarrow P(\mu)$, the distribution converges to Poisson Distribution with mean μ .

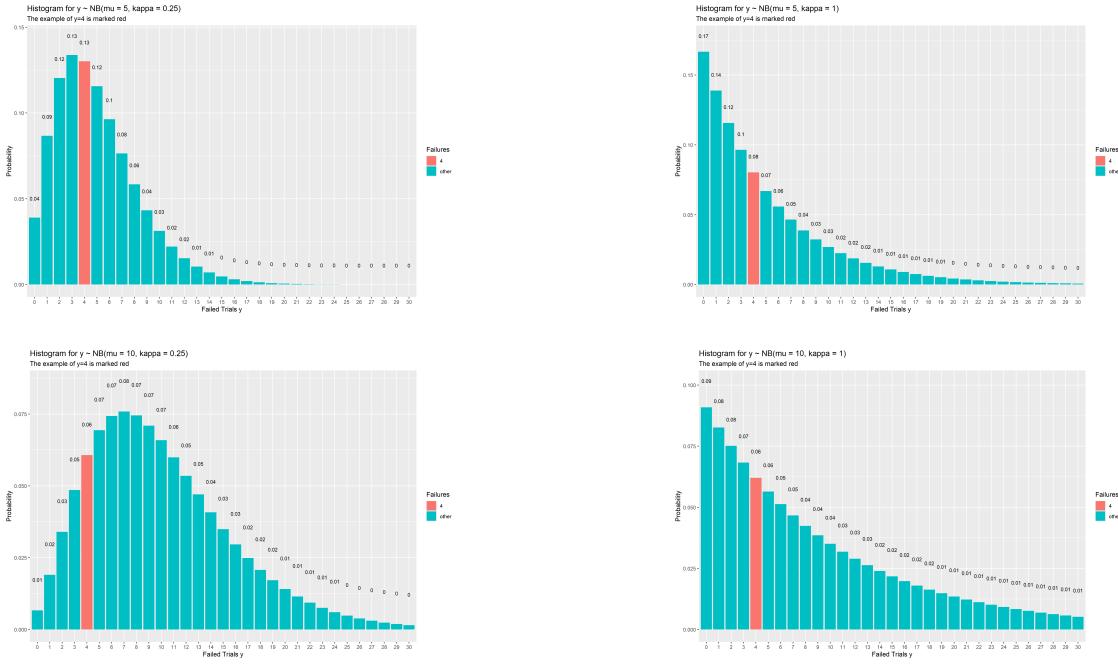


Figure 14: Negative Binomial Distribution PMF Histograms for NB(5,.25), NB(5,1), NB(10,.25), NB(10,1), respectively

This fascinating convergence property leads us to a significant topic of Negative Binomial Model: **Overdispersion**. We know that the mean and variance of Poisson Distribution is equal, and this is called **equidispersion**. This limits the Poisson Regression to a narrow feasible region since the raw data must have the same mean and the variance.

However, there is a quadratic term in the expression of variance of Negative Binomial Distribution, which brings the so called overdispersion, leading to a more flexible environment in modelling dispersed data. Therefore, **an important and necessary prerequisite of Negative Binomial Regression Model is the overdispersion of data**. We need to check this before starting the modeling process. If the dataset is not overdispersed, we might need to consider Poisson Regression Model instead.

3.1.3 Basic Concept of Negative Binomial Model

Negative Binomial Regression Model is a member of Generalized Linear Model (GLM). The response distribution belongs to the **exponential family**, where,

$$f(y) = c(y, \phi) \exp\left(\frac{y\theta - a(\theta)}{\phi}\right)$$

θ : Canonical Parameter ϕ : Dispersion Parameter

Note: Here the dispersion parameter ϕ is not same as the overdispersion parameter κ in the negative binomial distribution. For Negative Binomial Regression Model, the dispersion parameter is fixed.

Specifically, For $y \sim NB(\mu, \kappa)$,

$$\theta = \ln \frac{\kappa\mu}{1 + \kappa\mu}, \quad a(\theta) = -\frac{1}{\kappa} \ln(1 - \kappa e^\theta), \quad \phi = 1$$

$c(y, \theta)$ is generally not important in the estimation of the parameter during modelling process. The canonical parameter θ is commonly estimated when doing the negative binomial regression. This functional process is applied to many statistical analysis software such as R and SAS. We will see this later.

For our Negative Binomial Model, we choose the link function as natural log, i.e., $g(x) = \ln x$. Therefore, the structure of our negative binomial regression model is

$$\ln(\mathbb{E}[\mathbf{Y}]) = \mathbf{X}^T \boldsymbol{\beta}, \quad \text{where } Y \sim NB(\mu, \kappa) \quad (5)$$

\mathbf{Y} is the dependent variable (i.e., in our case, death count and exposure), and

$$\mathbf{X} = \begin{pmatrix} 1 & x_{11} & \cdots & x_{1p} \\ 1 & x_{21} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{np} \end{pmatrix} = (\mathbf{1}, \mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_p)$$

is the matrix of independent variables including the intercept(i.e., in our case, sexes, ages, years, etc.). $\boldsymbol{\beta}$ are the coefficients to be estimated [15].

3.1.4 Estimating Parameters: Maximum Likelihood Estimation

For the estimation of those coefficients mentioned above, we choose the **Maximum Likelihood Estimation (MLE)**.

Suppose that for each observation, we have a probability function $f(y_i; \theta, \phi)$. If our observations are independent, then the joint probability density function (pdf) is the multiple of each single probability function, that is,

$$F(y; \theta, \phi) = \prod_{i=1}^n f(y_i; \theta, \phi)$$

F is called the likelihood function. For Negative Binomial Regression Model, from (4) we have the likelihood function

$$F(y; \mu, \kappa) = \prod_{i=1}^n \frac{\Gamma(y_i + \frac{1}{\kappa_i})}{y_i! \Gamma(\frac{1}{\kappa_i})} \left(\frac{1}{1 + \kappa_i \mu_i} \right)^{\frac{1}{\kappa_i}} \left(\frac{\kappa_i \mu_i}{1 + \kappa_i \mu_i} \right)^{y_i}$$

Substituting the inverse link function $\mu_i = \exp(\mathbf{X}_i^T \boldsymbol{\beta})$,

$$F(y; \beta, \kappa) = \prod_{i=1}^n \frac{\Gamma(y_i + \frac{1}{\kappa_i})}{y_i! \Gamma(\frac{1}{\kappa_i})} \left(\frac{1}{1 + \kappa_i \exp(\mathbf{X}_i^T \boldsymbol{\beta})} \right)^{\frac{1}{\kappa_i}} \left(\frac{\kappa_i \exp(\mathbf{X}_i^T \boldsymbol{\beta})}{1 + \kappa_i \exp(\mathbf{X}_i^T \boldsymbol{\beta})} \right)^{y_i}$$

For the precision of the model, we want the observed dependent variable y , have the optimal “likelihood” to appear. Thus, all the partial derivatives of $F(y; \beta, \kappa)$ are trivialized to find the optimal. For the convenience of calculation, we take the log of this function to transform the multiplication to the accumulation:

$$\ell(y; \beta, \kappa) = \ln \sum_{i=1}^n \frac{\Gamma(y_i + \frac{1}{\kappa_i})}{y_i! \Gamma(\frac{1}{\kappa_i})} \left(\frac{1}{1 + \kappa_i \exp(\mathbf{X}_i^T \boldsymbol{\beta})} \right)^{\frac{1}{\kappa_i}} \left(\frac{\kappa_i \exp(\mathbf{X}_i^T \boldsymbol{\beta})}{1 + \kappa_i \exp(\mathbf{X}_i^T \boldsymbol{\beta})} \right)^{y_i} \quad (6)$$

This is called the **Log-Likelihood Function** of Negative Binomial Regression Model. The necessary condition for the optimization of log-likelihood function is:

$$\frac{\partial \ell}{\partial \boldsymbol{\beta}} = 0 \quad \text{and} \quad \frac{\partial \ell}{\partial \kappa} = 0$$

The parameters of Negative Binomial Model are estimated in this way in many statistical software such as R.

3.1.5 Offset

There is an important characteristic need to be pointed out is that the Negative Binomial Regression Model is for the modeling of **count data**. That is, the independent and dependent variables in the model need to be count data and belong to the positive integer domain. This characteristic appears because the negative binomial distribution is discrete.

In our case, the goal is to model the death rate in each year and for each age groups. The explanatory variables (e.g., years, ages, count of reason of death) are all count data. However, the response variable, which is the death rate, is a continuous data and cannot be implemented into this modeling process.

This problem is solved by the introduction of the concept called the **Offset**.

In view of that the number of death is count data and the death rate:

$$q_x = \frac{\text{Number of death}}{\text{Exposure}}$$

We can model the number of death instead of the death rate by some transformation based on the model of death rate. As illustrated in (5), the model of death rate can be written as:

$$\ln q_x = \ln \frac{d_x}{n} = \mathbf{X}^T \boldsymbol{\beta}$$

where d_x is the number of death and n is the exposure. Transfer the $\ln n$ to the RHS, we have:

$$\ln (q_x)_i = \ln (d_x)_i = \ln n_i + (\mathbf{X}^T \boldsymbol{\beta})_i \quad (7)$$

$\ln n_i$ in Equation (7) is called the offset. For this kind of offset model, the offset term generates a different intercept for every independent observation.

As stated by [4], offset terms are generally used to correct the different group sizes and different time periods of independent observations. In our case, exposure is one kind of group size for the observed number of people within the insurance policy. The offset term of the exposure efficiently correct the differences of number of observed people within different years and age groups.

3.2 Construction of Model

Since negative binomial regression is used for over-dispersion data (3.1.2), it is reasonable to test the over-dispersion of the data before modelling. Therefore, we run a Poisson Regression Model to check whether the data is over-dispersion or not.

```
>c<-deviance(fit) / df.residual(fit)
>c
[1] 7.164726
```

Table 2: Ratio of residual deviation to residual degrees of freedom (Female death count Model as example)

Over-dispersion is the case where the residual deviation is large relative to the degrees of freedom. In Table 2, c denotes the ratio of residual deviation to residual degrees of freedom. It is clear that the value of c is much greater than 1. Therefore, the model is over-dispersion and meets the negative binomial regression premise.

3.2.1 Offset and Non-offset Models

After confirming that the data was over-dispersion, we started to build the negative binomial regression model. As mentioned in section 3.1.5, there are two methods to build the model:

Method 1: Offset Model (take exposure as an offset term):

$$dx \sim \text{polynomial}(Age) + \text{polynomial}(Year) + \text{offset}(\log(\text{Exposure}))$$

Method 2: Non-offset Model (take exposure as a variable and model the exposure separately):

$$dx \sim \text{polynomial}(Age) + \text{polynomial}(Year) + \log(\text{Exposure})$$

$$\text{Exposure} \sim \text{polynomial}(\text{Age}) + \text{polynomial}(\text{Year})$$

Here $\text{polynomial}(x)$ means the polynomial that generated by the variable x , i.e.,

$$\text{polynomial}(x) = a_1x + a_2x^2 + a_3x^3 + \dots + a_nx^n$$

The goal of our modelling process is to ascertain the power n that makes models have the best goodness of fit. For convenience, Below we denote:

$$\text{poly}(x, n) = a_1x + a_2x^2 + a_3x^3 + \dots + a_nx^n$$

as the polynomial of variable x with the highest power of n .

(Moreover, we also tried to add some interactions and other variables such as $\text{Age} \times \text{Year}$, cause of death, smoking, etc. But they did not only make a marginal difference to the final model but also make the model more complex, so we decided not to include them in the model for efficiency.)

3.2.2 Likelihood Ratio Test

To assesses the goodness of fit of two competing models, we use the likelihood ratio test which is based on the ratio of their likelihoods.

The rationale of the likelihood ratio test is to compare the likelihood of two models by their ratio to see whether one of the model is significantly better than the other. The null and the alternative hypothesis of the Likelihood Ratio Test is [7]:

1. H_0 : Both the full and nested models fit the data equally well. In this case the nested model is simpler and the nested model should be chosen to avoid overfitting.
2. H_1 : The full model significantly outperforms the nested model in terms of data fit. In this case the full model should be chosen to ensure the performance of the model.

As stated before, the ratio of the likelihood is used as the criterion for the assessment of two models. Since we use log likelihood for the estimation of parameters, naturally, we can use the difference between the two log likelihood values as the test statistics (Since the ratio becomes subtraction when taking log function). If we denote the two log likelihood as ℓ_1 and ℓ_2 , then the test statistics:

$$\chi = 2(\ell_1 - \ell_2)$$

where the test statistics is constructed to make it fitted in the χ_q^2 distribution (q is the number of restrictions on coefficients). Thus the p-value of the test can be found in the table of chi-sqaure distribution.

In R, the better model can be selected by observing the number of significant digits. Here we take females as an example and choose Method 2. Two cases are listed here.

Case 1: Insignificant Case — choose the simplest model

```
Likelihood ratio test

Model 1: dx ~ poly(Year, 1) + poly(age, 4) + log(ex)
Model 2: dx ~ poly(Year, 2) + poly(age, 4) + log(ex)
#Df LogLik Df chisq Pr(>chisq)
1   8 -386.31
2   9 -385.62  1 1.3759    0.2408
```

Figure 15: Test in R output (Male death count Model as example)

(There are no significant digits. It means that these two models are similar, so we choose the simplest one. Therefore, model 1 is chosen in this example.)

Case 2: Significant Case — choose the most complete model

```

Likelihood ratio test

Model 1: ex ~ poly(Year, 1) + poly(age, 9)
Model 2: ex ~ poly(Year, 1) + poly(age, 10)
  #Df LogLik Df Chisq Pr(>Chisq)
1  12 -1616.1
2  13 -1607.9  1 16.401 5.126e-05 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Figure 16: Test in R output (Male Exposure Model as example)

(There are 3 significant digits, which means these two models are strongly different. Hence, we choose the most complete model. Obviously, model 2 is chosen in this example.)

Through the above methods, the following table shows the final models of offset and non-offset:

	Method 1 dx model	Method 2	
		dx model	Exposure model
Female	poly(Age,3)+poly(Year,2)+offset(log(exposure))	poly(Age,3)+poly(Year,2)	poly(Age,10)+poly(Year,1)
Male	poly(Age,4)+poly(Year,1)+offset(log(exposure))	poly(Age,4)+poly(Year,1)	poly(Age,10)+poly(Year,1)
Total	poly(Age,3)+poly(Year,2)+offset(log(exposure))	poly(Age,4)+poly(Year,2)	poly(Age,10)+poly(Year,1)

Table 3: Models of offset and non-offset

3.2.3 AIC & BIC Criteria

To measure which is better, the offset model or the non-offset model, we apply AIC and BIC as the measurement of the model statistics. Firstly, we introduce the AIC, which is called the Akaike information criterion.

For a specific model of some data, suppose that there are k estimated parameters and let L_{max} be the maximum likelihood function of the model. Then the AIC value is calculated in the following way:

$$AIC = 2k - 2 \ln L_{max}$$

It's a measure of the goodness of fit of a statistical model. The Akaike information criterion is based on the concept of entropy, the smaller the AIC, the better the model. Thus, the model with the smallest AIC is usually chosen.

			AIC	BIC
Female	Method 1	poly(Age,3)+poly(Yeay,2)+offset(log(exposure))	707.07	726.26
	Method 2	poly(Age,3)+poly(Year,2)+log(exposure)	697.49	725.13
Male	Method 1	poly(Age,4)+poly(Year,1)+offset(log(exposure))	793.61	817.98
	Method 2	poly(Age,4)+poly(Year,1)+log(exposure)	788.61	816.46
Total	Method 1	poly(Age,3)+poly(Year,2)+offset(log(exposure))	956.93	981.29
	Method 2	poly(Age,4)+poly(Year,2)+log(exposure)	944.95	976.28

Table 4: AIC and BIC of Table 3

The AIC value for Method 2 is slightly smaller than the one for Method 1 for all models. It shows that Method 2 is a better fit than Method 1. It indicates that the non-offset model is a better fit than the offset model.

On the other hand, there another criterion for the assessment of the model, called BIC (Bayesian information criterion):

$$BIC = k \ln n - 2 \ln L_{max}, \text{ where } n \text{ is the sample size}$$

whose value for Method 1 is marginally higher when compared to Method 2. Thus, with lower AIC and BIC values, the non-offset model is the better approach for the mortality rate data. The final models are:

	dx model	Exposure model
Female	$\text{poly}(\text{Age}, 3) + \text{poly}(\text{Year}, 2) + \log(\text{exposure})$	$\text{poly}(\text{Age}, 10) + \text{poly}(\text{Year}, 1)$
Male	$\text{poly}(\text{Age}, 4) + \text{poly}(\text{Year}, 1) + \log(\text{exposure})$	$\text{poly}(\text{Age}, 10) + \text{poly}(\text{Year}, 1)$
Total	$\text{poly}(\text{Age}, 4) + \text{poly}(\text{Year}, 2) + \log(\text{exposure})$	$\text{poly}(\text{Age}, 10) + \text{poly}(\text{Year}, 1)$

Table 5: Final Models

3.2.4 Modeling of Death Count

Using the package "glm" in **R** we can easily generate the fitted death count and the exposure, with those best model chosen above. In this section we display the output and the results of the death count model.

Fitted Negative Binomial Regression Model for death count

Call:																																												
<code>glm.nb(formula = dx ~ poly(Age, 3) + poly(Year, 2) + log(Exposure), data = FemaleMortality, link = log, init.theta = 4713.063641)</code>																																												
Deviance Residuals:																																												
<table> <thead> <tr> <th>Min</th> <th>1Q</th> <th>Median</th> <th>3Q</th> <th>Max</th> </tr> </thead> <tbody> <tr> <td>-2.0762</td> <td>-0.7109</td> <td>-0.3990</td> <td>0.4385</td> <td>3.0618</td> </tr> </tbody> </table>					Min	1Q	Median	3Q	Max	-2.0762	-0.7109	-0.3990	0.4385	3.0618																														
Min	1Q	Median	3Q	Max																																								
-2.0762	-0.7109	-0.3990	0.4385	3.0618																																								
Coefficients:																																												
<table> <thead> <tr> <th></th> <th>Estimate</th> <th>Std. Error</th> <th>z value</th> <th>Pr(> z)</th> </tr> </thead> <tbody> <tr> <td>(Intercept)</td> <td>-4.5189</td> <td>0.8071</td> <td>-5.599</td> <td>2.15e-08 ***</td> </tr> <tr> <td>poly(Age, 3)1</td> <td>21.9890</td> <td>1.4779</td> <td>14.879</td> <td><2e-16 ***</td> </tr> <tr> <td>poly(Age, 3)2</td> <td>6.5128</td> <td>1.4568</td> <td>4.471</td> <td>7.80e-06 ***</td> </tr> <tr> <td>poly(Age, 3)3</td> <td>-6.4808</td> <td>0.9049</td> <td>-7.162</td> <td>7.94e-13 ***</td> </tr> <tr> <td>poly(Year, 2)1</td> <td>3.4737</td> <td>0.5619</td> <td>6.182</td> <td>6.33e-10 ***</td> </tr> <tr> <td>poly(Year, 2)2</td> <td>-1.3593</td> <td>0.5107</td> <td>-2.662</td> <td>0.00777 **</td> </tr> <tr> <td>log(Exposure)</td> <td>0.6985</td> <td>0.1162</td> <td>6.009</td> <td>1.87e-09 ***</td> </tr> </tbody> </table>						Estimate	Std. Error	z value	Pr(> z)	(Intercept)	-4.5189	0.8071	-5.599	2.15e-08 ***	poly(Age, 3)1	21.9890	1.4779	14.879	<2e-16 ***	poly(Age, 3)2	6.5128	1.4568	4.471	7.80e-06 ***	poly(Age, 3)3	-6.4808	0.9049	-7.162	7.94e-13 ***	poly(Year, 2)1	3.4737	0.5619	6.182	6.33e-10 ***	poly(Year, 2)2	-1.3593	0.5107	-2.662	0.00777 **	log(Exposure)	0.6985	0.1162	6.009	1.87e-09 ***
	Estimate	Std. Error	z value	Pr(> z)																																								
(Intercept)	-4.5189	0.8071	-5.599	2.15e-08 ***																																								
poly(Age, 3)1	21.9890	1.4779	14.879	<2e-16 ***																																								
poly(Age, 3)2	6.5128	1.4568	4.471	7.80e-06 ***																																								
poly(Age, 3)3	-6.4808	0.9049	-7.162	7.94e-13 ***																																								
poly(Year, 2)1	3.4737	0.5619	6.182	6.33e-10 ***																																								
poly(Year, 2)2	-1.3593	0.5107	-2.662	0.00777 **																																								
log(Exposure)	0.6985	0.1162	6.009	1.87e-09 ***																																								
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1																																												
Null deviance: 1410.88 on 233 degrees of freedom																																												
Residual deviance: 200.52 on 227 degrees of freedom																																												
AIC: 697.49																																												
Number of Fisher Scoring iterations: 1																																												
2 x log-likelihood: -681.488																																												

Table 6: Fitted Negative Binomial Regression with GLM of Female Model

Call:
glm.nb(formula = dx ~ poly(Age, 4) + poly(Year, 1) + log(Exposure),
data = MaleMortality, link = log, init.theta = 6506.885421)
Deviance Residuals:
Min 1Q Median 3Q Max
-2.3714 -0.7757 -0.4566 0.4095 3.3004
Coefficients:
(Intercept) Estimate Std. Error z value Pr(> z)
(Intercept) -3.9755 0.9136 -4.352 1.35e-05 ***
poly(Age, 4)1 23.4101 1.4561 16.077 <2e-16 ***
poly(Age, 4)2 7.4497 1.9740 3.774 0.000161 ***
poly(Age, 4)3 -5.0755 1.1974 -4.239 2.25e-05 ***
poly(Age, 4)4 -2.4805 0.9009 -2.753 0.005898 **
poly(Year, 1)1 0.9886 0.4893 2.020 0.043350 *
log(Exposure) 0.6491 0.1287 5.045 4.55e-07 ***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Null deviance: 1795.51 on 239 degrees of freedom
Residual deviance: 239.04 on 233 degrees of freedom
AIC: 788.61
Number of Fisher Scoring iterations: 1
2 x log-likelihood: -772.614

Table 7: Fitted Negative Binomial Regression with GLM of Male Model

Call:
glm.nb(formula = dx ~ poly(Age, 4) + poly(Year, 2) + log(Exposure),
data = TotalMortality, link = log, init.theta = 90.37599788)
Deviance Residuals:
Min 1Q Median 3Q Max
-2.1813 -0.8591 -0.3615 0.4719 3.6182
Coefficients:
(Intercept) Estimate Std. Error z value Pr(> z)
(Intercept) -3.42574 0.74552 -4.595 4.33e-06 ***
poly(Age, 3)1 22.82746 1.07034 21.327 <2e-16 ***
poly(Age, 3)2 5.97018 1.43535 4.159 3.19e-05 ***
poly(Age, 3)3 -5.74883 0.86613 -6.637 3.19e-11 ***
poly(Age, 3)4 -1.87039 0.74356 -2.515 0.0119 *
poly(Year, 2)1 1.96411 0.40404 4.861 1.17e-06 ***
poly(Year, 2)2 -0.82650 0.37678 -2.194 0.0283 *
log(Exposure) 0.60175 0.09672 6.222 4.92e-10 ***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Null deviance: 2726.1 on 239 degrees of freedom
Residual deviance: 243.2 on 232 degrees of freedom
AIC: 944.95
Number of Fisher Scoring iterations: 1
2 x log-likelihood: -926.95

Table 8: Fitted Negative Binomial Regression with GLM of Male Model

Displayed above are regression coefficients against standard errors and p-values. All of the coefficients are statistically significant. These coefficients cannot be substitute directly into:

$$\text{Death Count} = \text{poly}(Age, 3) + \text{poly}(Year, 2)$$

Since R uses the simulated polynomials which is orthogonal, meaning that the data used in the variables are different from the original data.

Below are figures showing the comparison of the fitted model and the observed data.
 (All of these figures, the black line shows the observed data, and the red line shows the fit values.)

Female: $dx \sim \text{poly}(\text{Age}, 3) + \text{poly}(\text{Year}, 2) + \log(\text{exposure})$

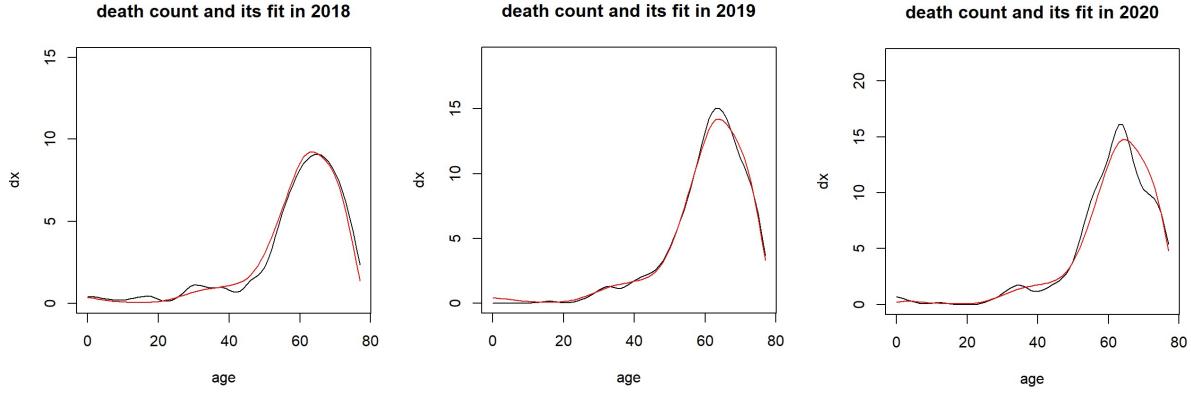


Figure 17: Female deaths in Ghana from 2018 to 2020 and the model fit values.

Male: $dx \sim \text{poly}(\text{Age}, 4) + \text{poly}(\text{Year}, 1) + \log(\text{exposure})$

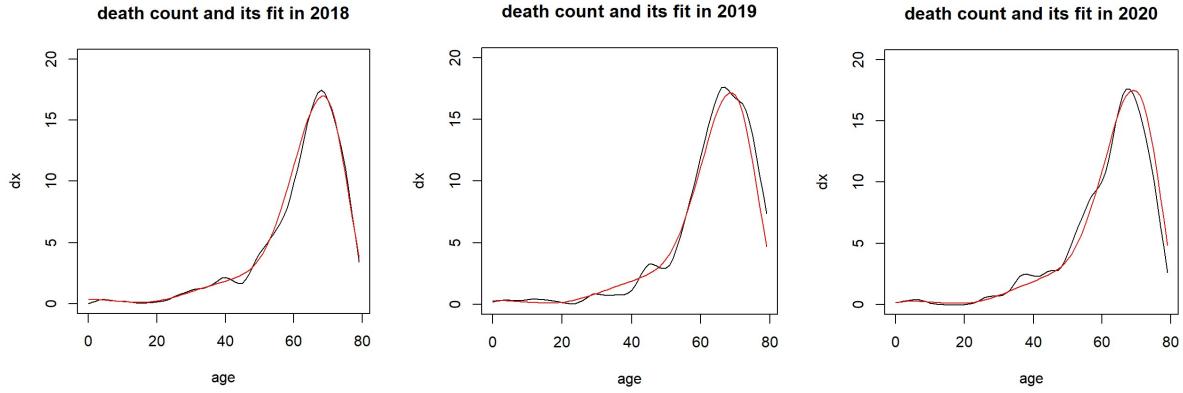


Figure 18: Male deaths in Ghana from 2018 to 2020 and the model fit values.

Total: $dx \sim \text{poly}(\text{Age}, 4) + \text{poly}(\text{Year}, 2) + \log(\text{exposure})$

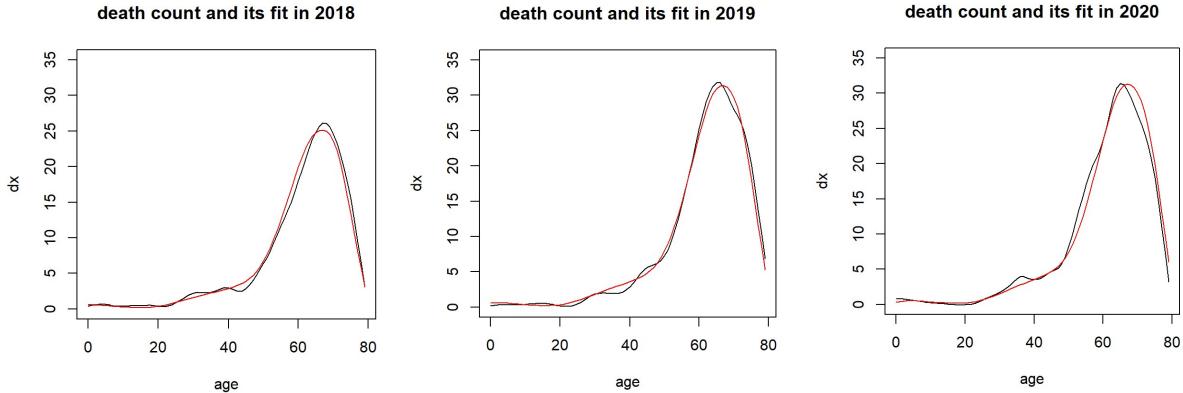


Figure 19: Total deaths in Ghana from 2018 to 2020 and the model fit values.

All the fitted red lines follow the observed values well. Although the exuberant overlap of fitted and observed lines may due to some overfitting issues, the likelihood ratio test already ensures that these models are not overfitted and the excellent fit is reasonable.

3.2.5 Modeling of Exposure

Similarly, we can construct all the fitted exposure models:

Fitted Negative Binomial Regression Model for death count

Call:				
glm.nb(formula = dx ~ poly(Age, 10) + poly(Year, 1) + log(Exposure), data = FemaleMortality, link = log, init.theta = 21.51466624)				
Deviance Residuals:				
Min	1Q	Median	3Q	Max
-2.1813	-0.8591	-0.3615	0.4719	3.6182
Coefficients:				
	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	6.74582	0.01436	469.617	<2e-16 ***
poly(Age, 10)1	3.45966	0.22196	15.587	<2e-16 ***
poly(Age, 10)2	-9.76409	0.22136	-44.110	<2e-16 ***
poly(Age, 10)3	-3.99631	0.22238	-17.970	<2e-16 ***
poly(Age, 10)4	2.28768	0.22303	10.257	<2e-16 ***
poly(Age, 10)5	-4.28564	0.22235	-19.275	<2e-16 ***
poly(Age, 10)6	-2.83808	0.22214	-12.776	<2e-16 ***
poly(Age, 10)7	4.62734	0.22228	20.818	<2e-16 ***
poly(Age, 10)8	-1.90433	0.22195	-8.580	<2e-16 ***
poly(Age, 10)9	-2.26861	0.22167	-10.234	<2e-16 ***
poly(Age, 10)10	0.45409	0.22158	2.049	0.0404 *
poly(Year, 1)1	-2.29198	0.21961	-10.437	<2e-16 ***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				
Null deviance: 3635.07 on 233 degrees of freedom				
Residual deviance: 248.09 on 222 degrees of freedom				
AIC: 3142.1				
Number of Fisher Scoring iterations: 1				
2 x log-likelihood: -3116.101				

Table 9: Fitted Negative Binomial Regression with GLM of Female Exposure Model

Call:	
glm.nb(formula = dx ~ poly(Age, 10) + poly(Year, 1) + log(Exposure), data = MaleMortality, link = log, init.theta = 23.7371402)	
Deviance Residuals:	
Min 1Q Median 3Q Max	
-7.6084 -0.5519 0.0225 0.5164 2.5260	
Coefficients:	
	Estimate Std. Error z value Pr(> z)
(Intercept)	6.83198 0.01352 505.430 <2e-16 ***
poly(Age, 10)1	2.17189 0.21182 10.254 <2e-16 ***
poly(Age, 10)2	-12.05922 0.21092 -57.174 <2e-16 ***
poly(Age, 10)3	-3.64765 0.21178 -17.224 <2e-16 ***
poly(Age, 10)4	4.46947 0.21221 21.062 <2e-16 ***
poly(Age, 10)5	-3.61470 0.21146 -17.094 <2e-16 ***
poly(Age, 10)6	-3.60740 0.21127 -17.074 <2e-16 ***
poly(Age, 10)7	4.09473 0.21146 19.364 <2e-16 ***
poly(Age, 10)8	-1.09219 0.21127 -5.170 2.35e-07 ***
poly(Age, 10)9	-1.07036 0.21107 -5.071 3.96e-07 ***
poly(Age, 10)10	0.87536 0.21107 4.147 3.36e-05 ***
poly(Year, 1)1	-2.53276 0.20929 -12.102 <2e-16 ***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1	
Null deviance: 5106.08 on 239 degrees of freedom	
Residual deviance: 254.55 on 228 degrees of freedom	
AIC: 3241.2	
Number of Fisher Scoring iterations: 1	
2 x log-likelihood: -3215.224	

Table 10: Fitted Negative Binomial Regression with GLM of Male Exposure Model

Call:	
glm.nb(formula = dx ~ poly(Age, 10) + poly(Year, 1) + log(Exposure), data = TotalMortality, link = log, init.theta = 21.43046644)	
Deviance Residuals:	
Min 1Q Median 3Q Max	
-7.6190 -0.5267 0.0221 0.4596 2.5195	
Coefficients:	
	Estimate Std. Error z value Pr(> z)
(Intercept)	7.45784 0.01409 529.443 <2e-16 ***
poly(Age, 10)1	1.90754 0.21970 8.682 <2e-16 ***
poly(Age, 10)2	-11.96058 0.21951 -54.488 <2e-16 ***
poly(Age, 10)3	-4.36712 0.22001 -19.850 <2e-16 ***
poly(Age, 10)4	3.01546 0.22028 13.689 <2e-16 ***
poly(Age, 10)5	-4.23537 0.21989 -19.261 <2e-16 ***
poly(Age, 10)6	-3.12804 0.21974 -14.235 <2e-16 ***
poly(Age, 10)7	4.31242 0.21980 19.620 <2e-16 ***
poly(Age, 10)8	-1.67986 0.21966 -7.648 2.05e-14 ***
poly(Age, 10)9	-1.43650 0.21952 -6.544 5.99e-11 ***
poly(Age, 10)10	0.95201 0.21947 4.338 1.44e-05 ***
poly(Year, 1)1	-2.36720 0.21818 -10.850 <2e-16 ***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1	
Null deviance: 4394.65 on 239 degrees of freedom	
Residual deviance: 249.66 on 228 degrees of freedom	
AIC: 3556	
Number of Fisher Scoring iterations: 1	
2 x log-likelihood: -3529.994	

Table 11: Fitted Negative Binomial Regression with GLM of Total Exposure Model

Below are figures showing the comparison of the fitted model and the observed data.

(All of these figures, the black line shows the observed data, and the red line shows the fit values.)

Female: $\text{ex} \sim \text{poly}(\text{Age}, 10) + \text{poly}(\text{Year}, 1)$

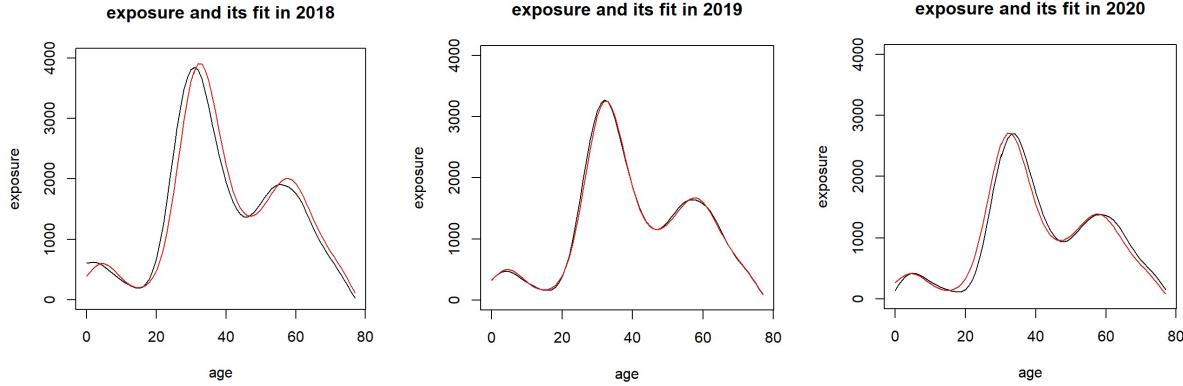


Figure 20: Female exposure in Ghana from 2018 to 2020 and the model fit values.

Male: $\text{ex} \sim \text{poly}(\text{Age}, 10) + \text{poly}(\text{Year}, 1)$

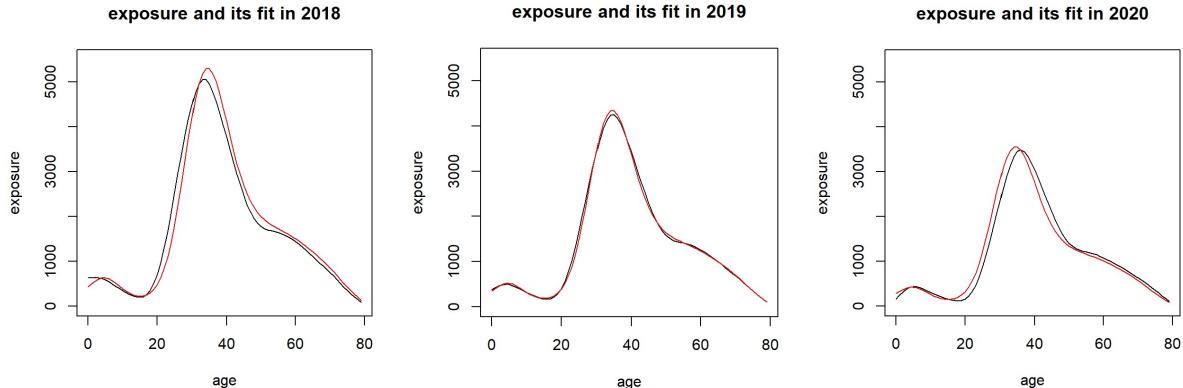


Figure 21: Male exposure in Ghana from 2018 to 2020 and the model fit values.

Total: $\text{ex} \sim \text{poly}(\text{Age}, 10) + \text{poly}(\text{Year}, 1)$

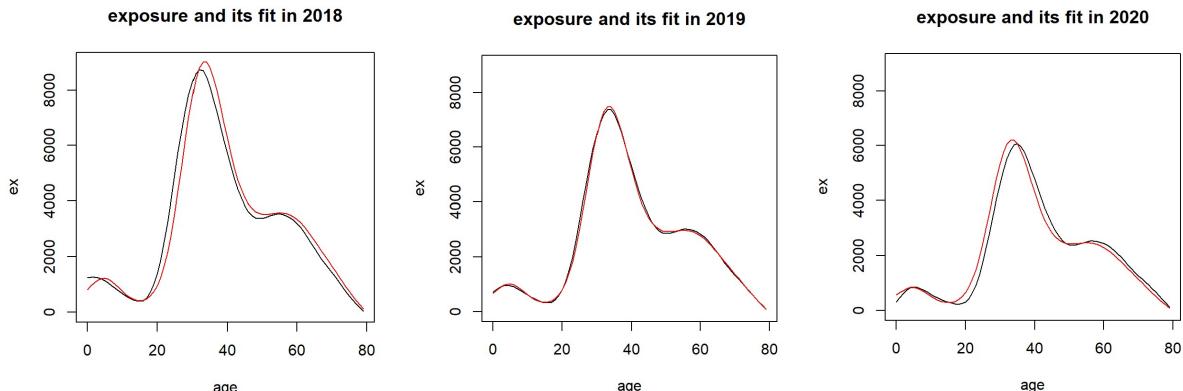


Figure 22: Total exposure in Ghana from 2018 to 2020 and the model fit values.

3.3 Fitted Mortality Rate

After modelling those variables, i.e., death count and exposure, separately, we can derive the fitted mortality rate by dividing the death count by the exposure. The complete 3D-plot will be shown at the process of modelling assessment. Displayed below are the example plots of log mortality rate versus the age for female and year from 2018 to 2020. The other plots follow the same pattern with the female plot. The blue points and the corresponding smoothed spline represent the observed mortality rate and the black ones represent the fitted mortality rate.

Similarly as the 3D log observed mortality rate, we add 0.001 to the mortality rate to deal with the zeros in the observed data. We can conclude from the plot that the fitted models fit well to the observed data. Most segments of the fitted spline approximately coincide with the observed one. If we analyse the pattern, the mortality rate declines mildly at the start, from age 0 to around 5, and the gradient becomes much less steep. At around age 25, the log mortality rate increases consistently and linearly, meaning that the mortality rate increases exponentially and at around age 78, the gradient becomes extremely steep.

In this chapter we do not consider the forecasting process. This is moved to the section 3.3, after analysing some problems of the model in order to simplify and format the forecasted data better.

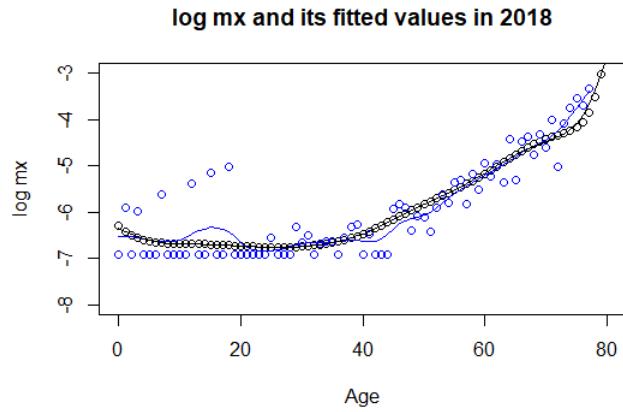


Figure 23: Fitted mortality rate for female in 2018

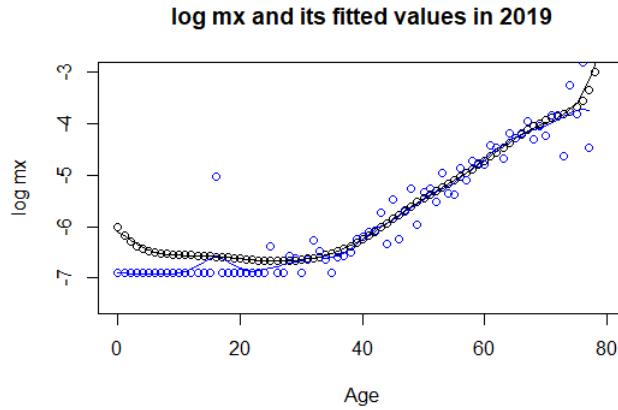


Figure 24: Fitted mortality rate for female in 2019

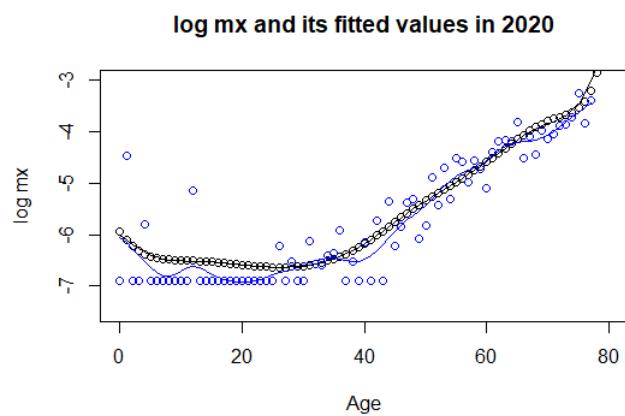


Figure 25: Fitted mortality rate for female in 2020

4 Model Assessment

4.1 Residual Analysis

Residuals, where $\epsilon_i = y_i - \hat{y}_i$, are commonly used for analysing the goodness of fit for general linear models. Models fit well when the residuals are normally distributed. However, for generalized linear models, the assumptions are not the same as general linear models, which means that the original definition of residuals are not suitable for the analysis of our negative binomial model. Below are some generalized residual forms that used in the Negative Binomial Regression Model assessment.

4.1.1 Deviance Residual

Deviance Residual is derived based on the comparison of fitted model and saturated model. The **saturated model** is defined as the perfect fitted model that making every prediction equal to the observed value. From (6) we can see that the log-likelihood function for exponential family:

$$\ell(y; \theta, \phi) = \ln \sum_{i=1}^n c(y_i, \phi) \exp \left(\frac{y_i \theta_i - a(\theta_i)}{\phi} \right) = \sum_{i=1}^n \left[\ln c(y_i, \phi) + \frac{y_i \theta_i - a(\theta_i)}{\phi} \right]$$

Therefore, to make every estimator saturated:

$$\frac{\partial l}{\partial \theta_i} = \frac{y_i - a'(\theta_i)}{\phi} = \frac{y_i - \mu_i}{\phi} = 0$$

where $a'(\theta_i) = \mu_i$, the expectation for each observation. Thus, the maximum likelihood estimator for the saturated model is $\check{\theta}_i$ defined as above. The saturated log-likelihood is:

$$\check{\ell}(y; \theta, \phi) = \sum_{i=1}^n \left[\ln c(y_i, \phi) + \frac{y_i \check{\theta}_i - a(\check{\theta}_i)}{\phi} \right]$$

If we denote the log-likelihood of our fitted model as \hat{l} , the deviance can be calculated as:

$$\Delta \equiv 2 (\check{\ell} - \hat{l}) \quad (8)$$

As a direct intuition, if the model provides a good fit then the log-likelihood of the model should be close to the saturated one, resulting that the absolute value of deviance should relatively be small. For exponential family, the deviance:

$$\Delta = 2 \sum_{i=1}^n \left[\frac{y_i(\check{\theta}_i - \hat{\theta}_i) - a(\check{\theta}_i) + a(\hat{\theta}_i)}{\phi} \right]$$

Specifically, as provided by [4], for Negative Binomial Model:

$$\Delta = 2 \sum_{i=1}^n \left[y_i \ln \left(\frac{y_i}{\hat{\mu}_i} \right) - \left(y_i + \frac{1}{\kappa} \right) \ln \left(\frac{y_i + \frac{1}{\kappa}}{\hat{\mu}_i + \frac{1}{\kappa}} \right) \right] \quad (9)$$

This is called the **Residual Deviance** and is shown at the output of modelling procedure in R. What is illustrated simultaneously with this data is the **Null Deviance** Δ_N , calculated by the same formula with (8), substituting the saturated log-likelihood with the log-likelihood of the model with only intercept term.

```
(Dispersion parameter for Negative Binomial(21.5147) family taken to be 1)

Null deviance: 3635.07 on 233 degrees of freedom
Residual deviance: 248.09 on 222 degrees of freedom
AIC: 3142.1

Number of Fisher Scoring iterations: 1

Theta: 21.51
Std. Err.: 2.15

2 x log-likelihood: -3116.101
```

Figure 26: Null Deviance & Residual Deviance in R output (Female Exposure Model as example)

[14] stated that we can compare the value of null deviance and residual deviance to analysis the goodness of fit by the test statistics:

$$\mathbf{X}^2 = \Delta_N - \Delta, \quad \text{where } \mathbf{X}^2 \sim \chi_p^2$$

where $p = r - n$ (r is the df of residual deviance and n is the df of null deviance) is the difference of degree of freedom between null and residual deviance, indicating the number of explanatory variables. If the p-value for this test statistics is significantly small, the model provides a good fit. R codes are shown in the Appendix A and the results are concluded in the Table below:

Model	Null & df	Residual & df	test stat & df	p-value
Female dx	1410.88 (233 df)	200.52 (227 df)	1210.36 (6 df)	0.000000
Female Exposure	3635.07 (233 df)	248.09 (222 df)	3386.98 (11 df)	0.000000
Male dx	1795.51 (239 df)	239.04 (233 df)	1556.47 (6 df)	0.000000
Male Exposure	5106.08 (239 df)	254.55 (228 df)	4851.53 (11 df)	0.000000
Total dx	2726.1 (239 df)	243.2 (232 df)	2482.9 (7 df)	0.000000
Total Exposure	4394.65 (239 df)	249.66 (228 df)	4144.99 (11 df)	0.000000

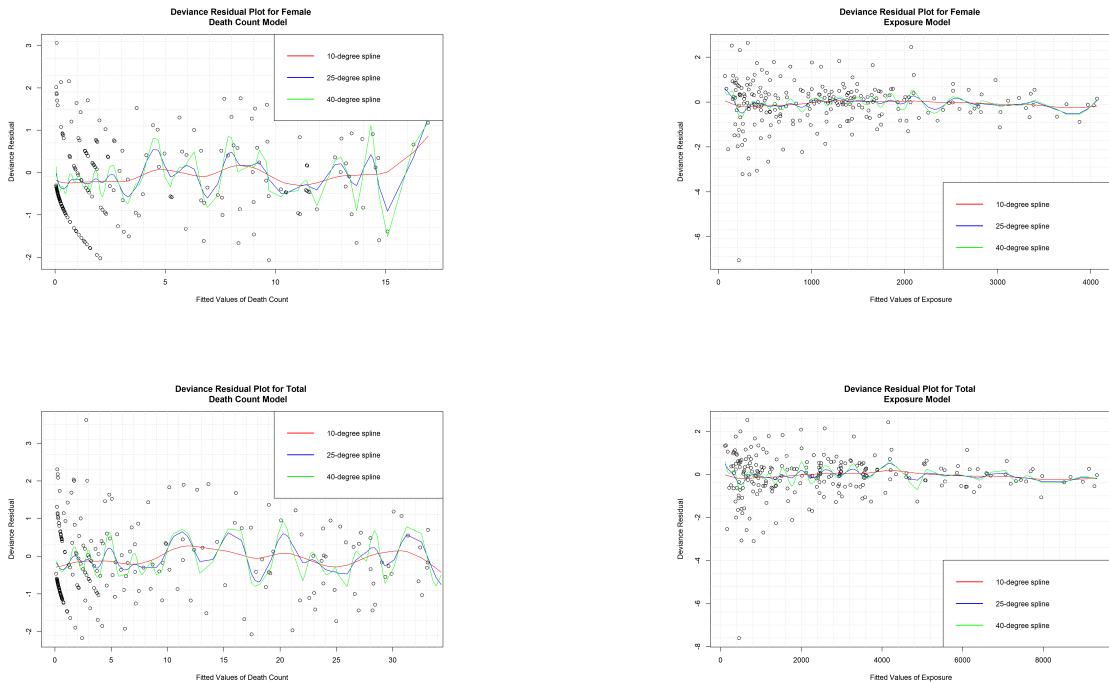
Table 12: χ^2 -test for Null and Residual Deviance

All the p-values illustrated are strongly significant, meaning that all the models give decent goodness of fit.

Barring the Residual Deviance Analysis, we can also analysis the deviance individually. For each observation, we have the deviance:

$$\delta_i^2 = 2 \left[y_i \ln \left(\frac{y_i}{\hat{\mu}_i} \right) - \left(y_i + \frac{1}{\kappa} \right) \ln \left(\frac{y_i + \frac{1}{\kappa}}{\hat{\mu}_i + \frac{1}{\kappa}} \right) \right]$$

the square root of which, i.e., δ_i , is called the **Deviance Residuals**. The sign is given by the sign of $y_i - \hat{\mu}_i$. The distribution of deviance residuals is skewed for GLM [6]. Thus, we need other criterion for analysing this residual. As mentioned above, $\delta_i \sim \chi_{r-n}^2$. Remember that: $\mathbb{E}[X] = r - n$ for $X \sim \chi_{r-n}^2$. Therefore, for large r , we expect that every single value of residual deviance, contributes approximately $\frac{r-n}{n} \approx 1$ to the deviance residual. Thus one criterion for this residual is that δ_i is not much greater than 1 or less than -1 [4], otherwise the observation contributes too much to the model, which due to a lack of fit. The residual also cannot show any manifest pattern. These two requisites can be shown by the Fitted Value VS Residual plot shown below.



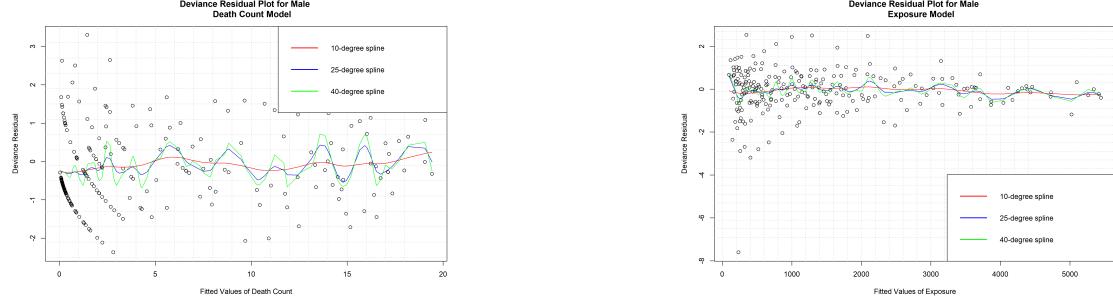


Figure 3: Plot and splines of fitted values VS deviance residuals (Row1: Female Data Row2: Male Data Row3: Total Data, dx plot on the left and Exposure model on the right)

There are three splines shown in the figure. We choose the 25-degree (blue) one to analysis since the 40-degree (green) one may due to some overfitting.

As shown in the figure, for death count deviance residuals, the death count residual figure shows some inverse function pattern at the lower tail intuitively. This may due to lack of data for age 0-10. However, the splines shows that there are no clear pattern for the residuals. No residuals are much greater than 3, meaning that the deviance residual behaves well generally.

For Exposure deviance residuals, The splines also indicate that there are no clear pattern. However, apparently there is one single observation that contributes too much to the modelling process. This one observation, nevertheless, makes small difference on the basis of over 200 observations.

In conclusion, the residual deviance and the deviance residual behaves well generally, with some minor discrepancies with the criterion for deviance residuals of exposure.

4.1.2 Anscombe Residual

As illustrated above, we cannot analysis residual deviance through normality test. There are two substitutions for this residuals, which simulate residuals in standardized spaces in order to make them approximately normally distributed. In this section we will analyze the so called Anscombe Residuals.

The Anscombe Residual is calculated as:

$$A(y_i) = \frac{h(y_i) - h(\hat{y}_i)}{\dot{h}(\hat{y}_i) \sqrt{V(\hat{y}_i)}}$$

where $\dot{h}(y) = V(y)^{-\frac{1}{3}}$ so that $h(y)$ is approximately normally distributed. $V(\mu)$ is the variance function of the response distribution. [4] mentioned that the approximate normality of Anscombe residual can be checked through the quantile-quantile plot (QQ-plot). Below are examples of QQ-plots of Female dx and Exposure model. The remaining QQ-plot follows the similar pattern and are not illustrated for avoiding repetition.

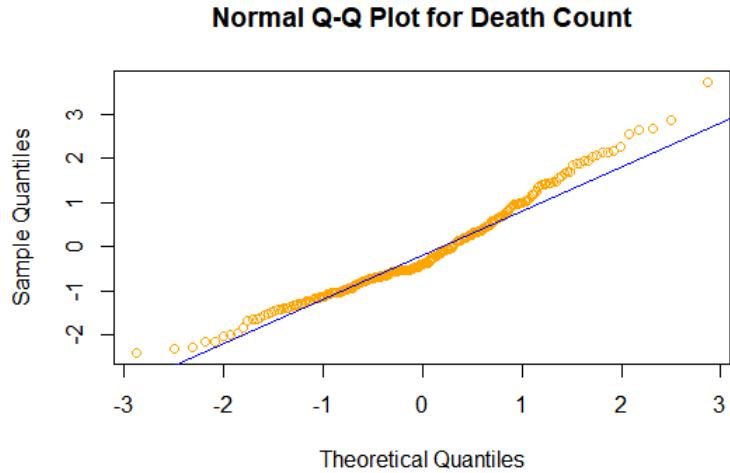


Figure 27: Q-Q Plot for Female Death Count Model

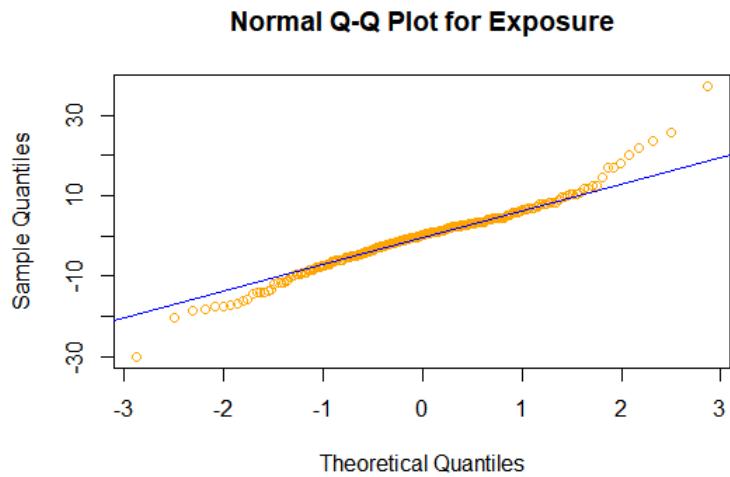


Figure 28: Q-Q Plot for Female Exposure Model

The Quantile-Quantile residual plots both approximately follow the straight line, with some minor deviation at both tails, which indicates that our model fits well, but the negative binomial model does not completely capture the historical trend of death count and exposure.

However, this graphical consilience does not make the Anscombe Residual successfully pass the formal Anderson-Darling Normality Test. As we can see in Table 13, the p-values are significantly small, illustrating the strong non-normality of both residuals, which is discrepant with the intuitive graphical analysis.

Model	Test Statistics	p-value
Female dx	2.8977	2.644e-07
Female Exposure	1.9973	4.229e-05
Male dx	4.0666	3.816e-10
Male Exposure	1.8546	9.484e-05
Total dx	2.7932	4.764e-07
Total Exposure	1.827	0.0001109

Table 13: Anderson-Darling Test for Anscombe Residuals (ansresdx: Residual for Death Count model, ansresex: Residual for Exposure model)

This discrepancy can be shown by the histogram of Anscombe Residual. As shown in Figure below, the Anscombe Residuals are apparently right-skewed marginally, leading to the non-normality result of Anderson-Darling Test.

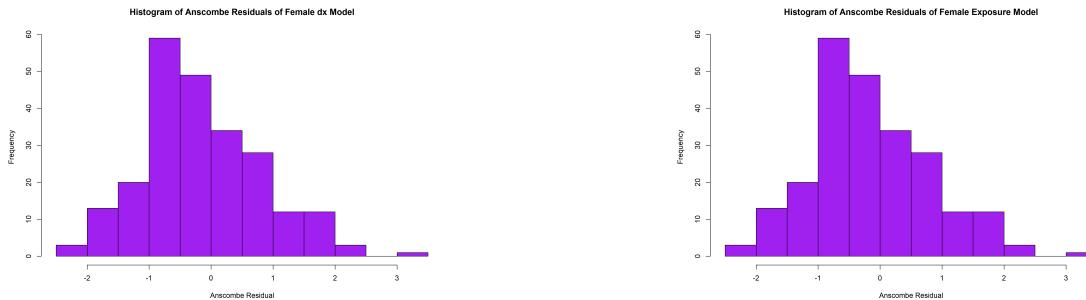


Figure 29: Histogram for the Anscombe Residuals (Female Data Examples)

4.1.3 Simulated Residual: DHARMA Package

The bad behaviour, i.e., the marginal non-normality of Anscombe Residual is explained by [11], that Anscombe Residual and Deviance residual are numerically similar, which leads to the similar distribution of Anscombe Residual and Deviance Residual. Even the best-fitted regression model for count data has non-normal Deviance Residual [9]. This problem leads us to find another substitution for Deviance and Anscombe Residual to process the residual normality test.

Recently [8] provides well-behaved standardized residuals for hierarchical (multi-level/mixed) regression models, where the Negative Binomial Regression Model falls into this category. Hartig provides a powerful R package called the DHARMA package, which can generate analytical graphs for this kind of simulated residual. In this section, we will focus on these R packages and the generated figures for the final diagnostics of residual.

Now we focus on the Death Count Model. The R command in DHARMA Package `simulateResiduals()` provides a graphical visualization of the information of this residual, including the Q-Q Plot, the fitted values VS residuals plot, its quantile splines, etc. Below are sequentially the DHARMA residual plots for female, male and Total data.

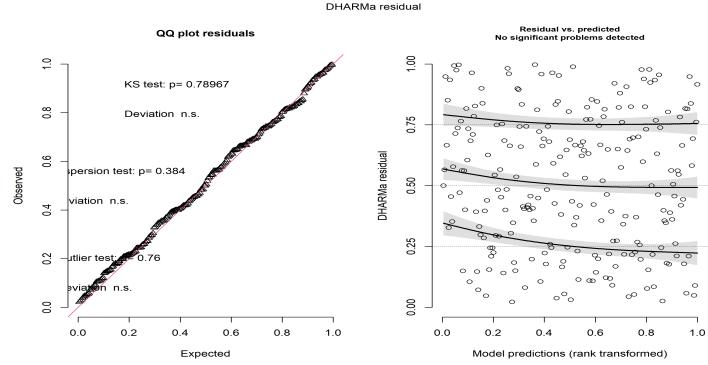


Figure 30: DHARMA Residual Plot for Female dx Model

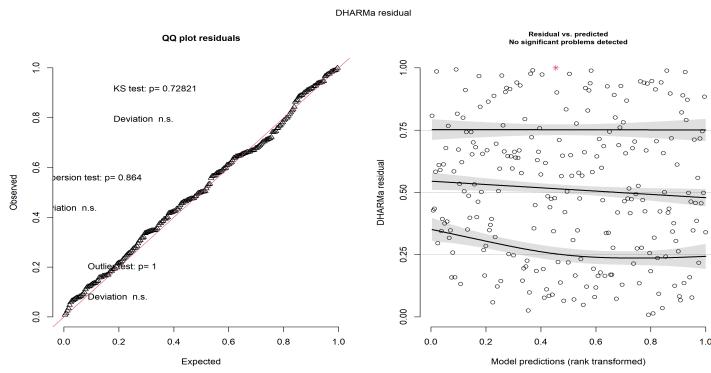


Figure 31: DHARMA Residual Plot for Male dx Model

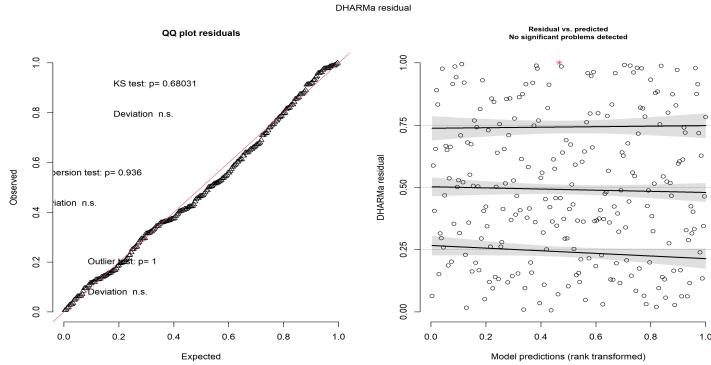


Figure 32: DHARMA Residual Plot for Total dx Model

Now the residuals suit much better to the normal pattern compared with the Anscombe Residual Plots, which can be seen through the figures at left. From the right figures, the DHARMA residuals are randomly distributed throughout the space and the three smoothed quantile lines show no manifest pattern and they all go straight approximately.

However, for the Exposure models, there are some inconsistencies detected by the DHARMA residuals. Shown below are the corresponding three DHARMA residual plots for three exposure models.

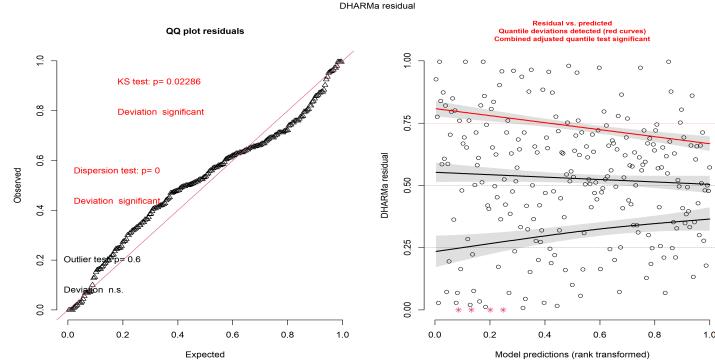


Figure 33: DHARMA Residual Plot for Female Exposure Model

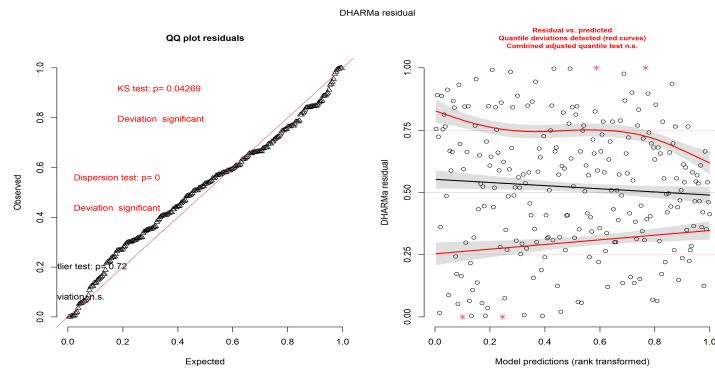


Figure 34: DHARMA Residual Plot for Male Exposure Model

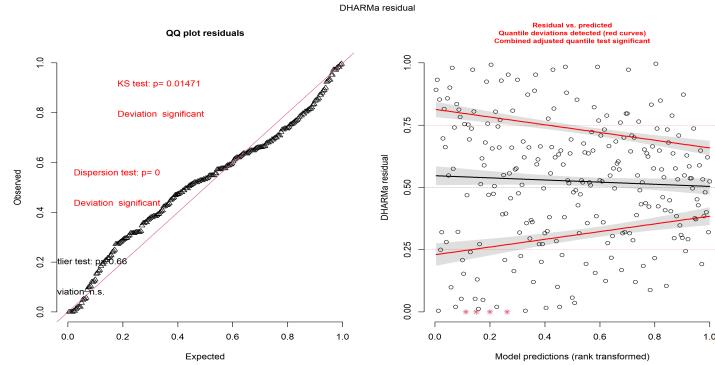


Figure 35: DHARMA Residual Plot for Total Exposure Model

From the left Q-Q Plots, the DHARMA residuals accumulate more around 0.4-0.6 than the lower and upper tails, indicating some underdispersion of the residuals, which illustrates that the Negative Binomial Regression Model may not capture the historical trace of Exposure decently. From the left figures, i.e., the residual plots, the 3 quantile lines converge with the increase of exposure, meaning that some heteroskedasticity appears in the residual pattern. Both indicate that some assumptions of the negative binomial model may be violated for the three Exposure Models.

Furthermore, DHARMA Package provides a rigorous way to go through the residual non-parametric dispersion test

by the R command `testDispersion()`. Below are three graphs generated by this R dispersion test command, for the models belonging to three datasets.

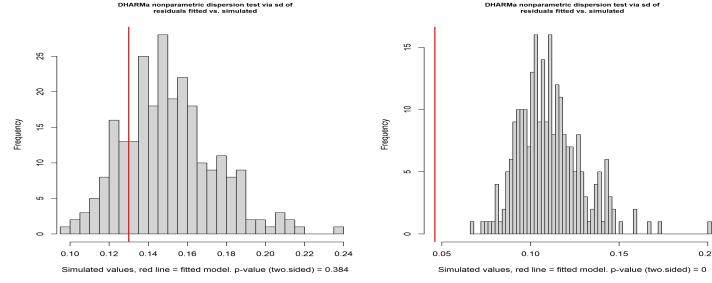


Figure 36: DHARMA Dispersion Test for Female dx (left) and Exposure (right) Models

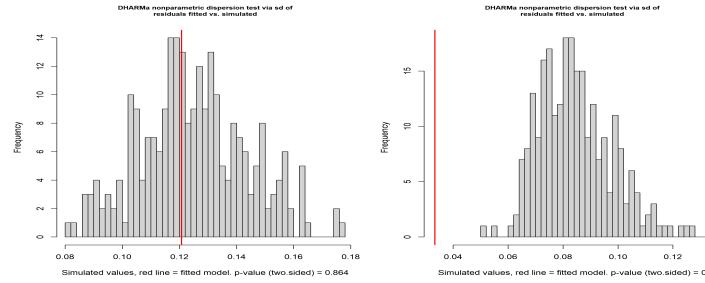


Figure 37: DHARMA Dispersion Test for Male dx (left) and Exposure (right) Models

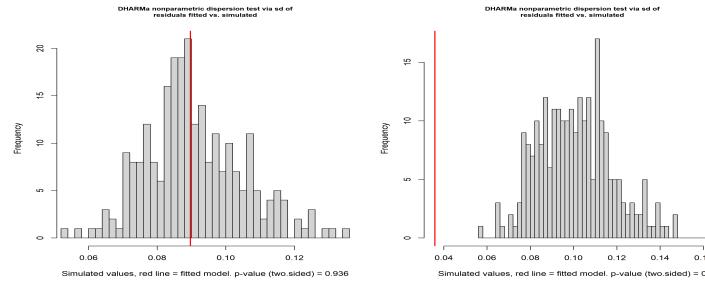


Figure 38: DHARMA Dispersion Test for Total dx (left) and Exposure (right) Models

Indeed, the DHARMA Residuals for the exposure models face the problem of underdispersion for the fitted variance line falls below the histogram of residuals, meaning that the variance is significantly small than the mean of the residual. Barring from that, the dx models pass through the dispersion test successfully and the simulated variance lines falls into the histograms.

Two ways for avoiding this problem of the exposure model were considered by us:

- Increase or decrease the power of the polynomial used in the exposure model to cater for the decent DHARMA residual pattern.
- Use the offset models, thus avoiding the models for exposures.

However, after trying the first methods, the pattern of the DHARMA residuals for exposure models is still discontented. Moreover, increasing or decreasing the power of our chosen model may be due to overfitting or underfitting, respectively, which escalates the inaccuracy of models.

Indeed, as long as the model gives a good fit, some minor heteroskedasticity in the residual pattern does not influence significantly to the inaccuracy or prediction of our model. Thus, in view of the non-offset models performing better on the value of AIC and BIC, it is preferred to choose the non-offset ones. Thus the second method: using the offset model, is also not in consideration.

4.2 Upper Tail Assessment

As mentioned in section 2.4, the raw data set is due to a significant lack of data at the lower tail and the upper tail. Since the mortality rate of the lower tail is small, the lack of data, which leads to the 0s in the mortality rate, does not affect much to the final result much. However, we have many 0 data or a small database around the upper tail, whilst the mortality rate around this age group is much greater than 0, this affects that the mortality rate begins to decrease at the lower tail drastically, which is not discrepant with the reality. Below is the example graph for the fitted mortality rate of females versus the age in 2018 (including the age group from 81 to 100 forecasted by the fitted model).

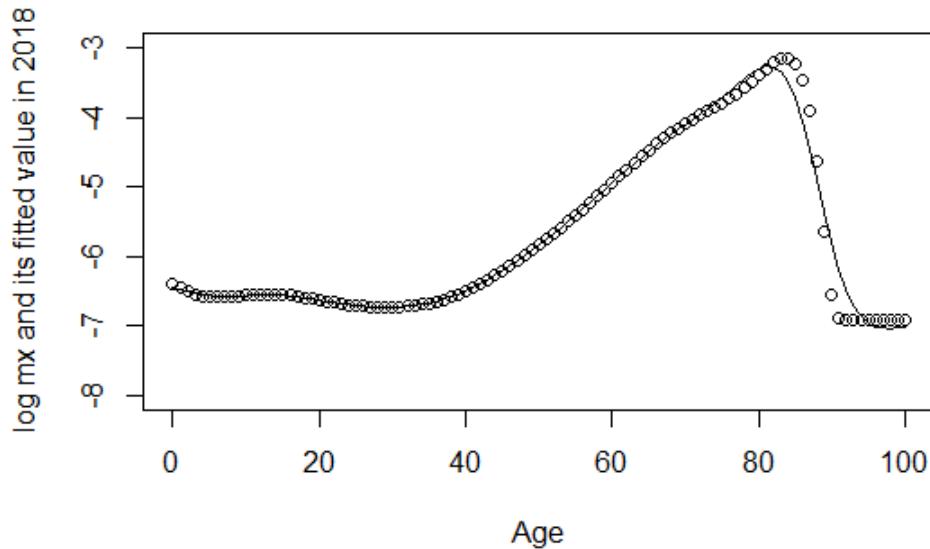


Figure 39: The drastic decline at the upper tail of age variable

As mentioned before, the fitted mortality rate is also added by 0.001 to avoid the zeros that made the value $\log(\text{mortality rate})$ invalid. The plunging pattern forecasts that people who are alive to about 82 years old have a very small possibility to die afterwards. This is absolutely inconsistent with reality. This may be due to two reasons:

- Lack of data between the age group 70 to 80, leading to the decline of the further forecast of the age group mortality rate values.
- The innate character of the Negative Binomial Model. Since we use the model of age polynomial for 4, the curve should turn the direction (i.e., the gradient should turn from positive to negative (or vice versa) four times. If we analyse the pattern, before age 80, the curve changes the direction for 3 times, at around age 4, age 18 and age 38, respectively. The final change then happens in the forecasting area.

This problem cannot be effectively solved since we are not provided more data for the 80s to 100s. Therefore, the construction of the mortality table is constrained to halt at age 80. Due to this intractable problem, We only do the forecast in the year (from 2021 to 2025), but not in age.

4.3 Forecasting and assessment

Now we do the forecasting process formally, ranging from the year 2021 to 2025, and age 0 to 80. This process was done in R by the command "predict.glm". The complete R program is displayed in the Appendix below. The generated variables are all calculated by the model we constructed above. Suppose that for our model:

$$N = f(a) + g(b) + \log(c)$$

$$c = F(a) + G(b)$$

where a represents the age variable, and b represents the year variable. N is the death count and c is the exposure. Therefore, the first equation represents our death count model and the second equation is the exposure model. Then, the "predict.glm" function generate the forecasted mortality rate $N_{forecast}$ at the age i and year j by the formula:

$$N_{forecast} = \frac{N}{c} = \frac{f(a) + g(b) + \log(c)}{F(a) + G(b)} = \frac{f(a) + g(b) + \log(F(a) + G(b))}{F(a) + G(b)}$$

Below are the 3D plots for the fitted and forecasted mortality rate versus age and year for female, male, and combined sex data.

Fitted and Forecasted m_x for females from 2018 to 2025

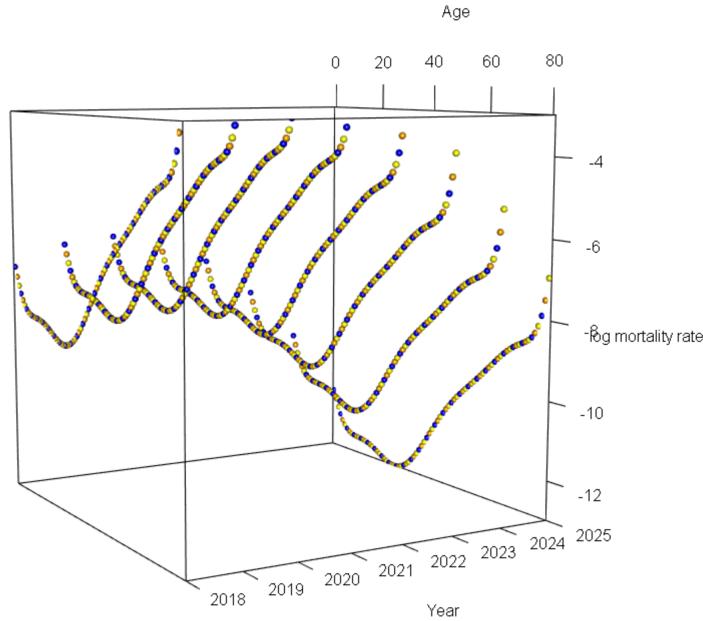


Figure 40: Fitted and forecasted mortality rate for female data

Fitted and Forecasted m_x for males from 2018 to 2025

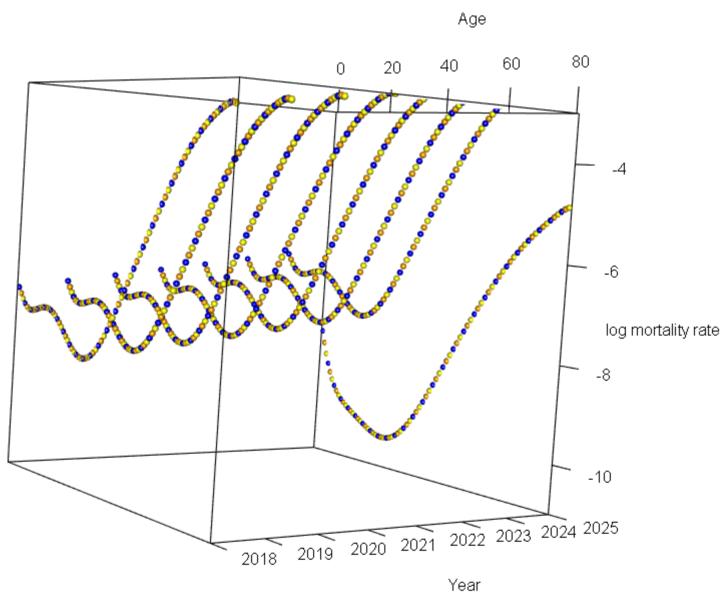


Figure 41: Fitted and forecasted mortality rate for male data

Fitted and Forecasted m_x for combined sex data from 2018 to 2025

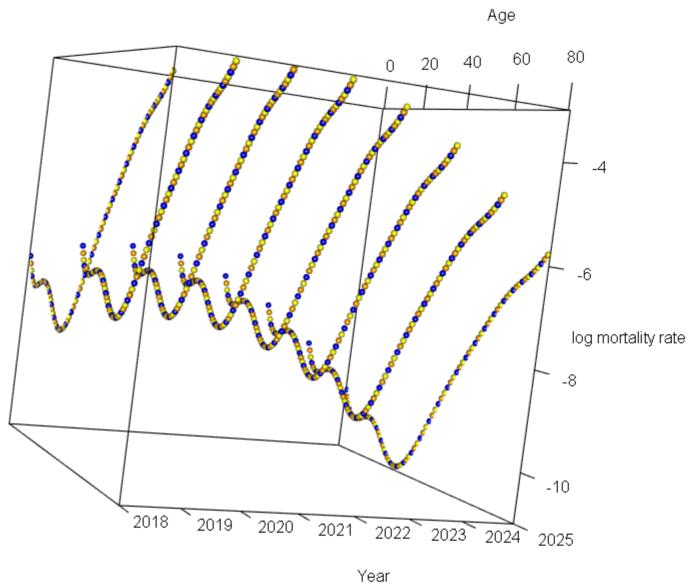


Figure 42: Fitted and forecasted mortality rate for combined sex data

Barring the male mortality rate plot, which increases steadily from 2018 to 2025 in almost all age intervals and an abrupt plummet in 2025, the other mortality rates experience a mild increase from 2018 to 2020, and a mild decrease from 2021 to 2022. Then, the mortality rate experiences a plunge similar to a quadratic pattern. This pattern leads to the prediction of the mortality rate after 2023 is significantly not consistent with reality, even leading to the result that only less than 1000 people died in 100000 people after 80 years of life (derived when constructing the mortality table, by the variable l_x). This may be due to some reasons:

- We only have 3 years observed data set, but our prediction has a time span of 5 years. The lack of data in the time span leads to the coefficient for the year is extremely large and the model is very sensitive to the small change in the year.
- The innate character discussed before, said that the mortality rate has only one gradient change during the time span from 2018 to 2025, meaning that the mortality rate will continuously decrease.

Therefore, due to this problem, we construct a reasonable prediction of the mortality table only spanning from 2021 to 2022, with the original fitted data from 2018 to 2020.

5 Construction of Mortality Table

After the data processing and the modelling process, we are ready to construct the final mortality table, which is the ultimate goal of our project. In this section, we are going to define all the parameters displayed in the mortality table and illustrate our final result.

5.1 Definition of Parameters

Except for the Age, Year and mortality rate, there is also many other important information stored in many extra variables proffered by the mortality table. Below is the table concluding all the variables and the definitions contained in the mortality table. These formulae are provided by [13] who provide the formulae of the mortality table in HMD (Human Mortality Database).

Parameter	Formula	Definition
m_x	$m_x = \frac{d_x}{E_x}$	The life table death rates
q_x	$q_x = \frac{m_x}{1+(1-a_x)m_x}$	The probability of death
d_x	$d_x = l_x q_x$	The distribution of deaths by age in the life-table population
L_x	$L_x = l_x - (1 - a_x)d_x$	The person-years lived by the life-table population in the age interval $[x, x + 1]$
a_x	$a_x = \frac{1}{2}$ for all single-year ages except age 0	The estimated average age at death of those dying in the x th year of life
p_x	$p_x = 1 - q_x$	The probability of surviving from age x to $x + 1$
l_x	$l_x = l_0 \prod_{i=0}^{x-1} p_i$	The number of survivors (out of 100,000) at ages $x > 0$
T_x	$T_x = \sum_{i=x}^{109} +\infty L_x$ ($+\infty L_x = l_{110} a_{110}$)	The person-years remaining for individuals of age x for $x = 0, 1, \dots, 109..$ For the open age category, $+\infty T_x = +\infty L_x$
e_x	$\circ e_x = \frac{T_x}{l_x}$	Remaining life expectancy at age x

Table 14: Parameters in Mortality Table

Firstly, the two most confusing variables in the mortality table are the mortality rate m_x , and the death rate d_x . The specific distinction is described as below:

- m_x : Known as the central mortality. The average number of deaths each year at age x last birthday in the relevant year period, divided by the average population at that age over the same period.
- q_x : The probability that a person exact age x will die within one year.

Secondly, as mentioned in the formula table above, $a_x = \frac{1}{2}$ for all single-year ages except age 0. Since for age 0, the possible death period is much accumulated around the time that the child was just born, which is different from other age period, when the death is happened uniformly during the one-year period. Therefore, we have alternative formulae for the age 0. [13] provides a empirical formulae for the calculation of a_0 , which is shown as the table below:

Table 15: Andreev-Kingkade formulas for computing a_0 given m_0

m_0 range	Formula: $a_0 = a + bm_0$
Males	
$[0, 0.02300)$	$0.14929 - 1.99545m_0$
$[0.0230, 0.08307)$	$0.02832 + 3.26021m_0$
$[0.08307, \infty)$	0.29915
Females	
$[0, 0.01724)$	$0.14903 - 2.05527m_0$
$[0.01724, 0.06891)$	$0.04667 + 3.88089m_0$
$[0.06891, \infty)$	0.31411

For a Combined-sex life table, we compute a_0 as follows: $a_0^T = \frac{a_0^F D_0^F + a_0^M D_0^M}{D_0^F + D_0^M}$ where the superscripts F , M , and T denote values for the female, male, and total populations, respectively, and where D_0^i refers to all deaths at age zero (both lower and upper triangles) for population i .

5.2 Result Table

With those parameter provided above, we can calculate all these variables in R and construct the final mortality table. The complete R code is provided in the Appendix.

Table 16: Combined Sex Life Table in 2018
 National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2018	0	0.000671727	0.000671342	67.13421607	99942.77448	0.1475953	0.999328658	100000	7696624.613	76.96624613
2018	1	0.000575164	0.000574999	57.46128789	99904.13514	0.5	0.999425001	99932.86578	7596681.838	76.01785237
2018	2	0.000498049	0.000497925	49.73048443	99850.53925	0.5	0.999502075	99875.4045	7496777.703	75.06130004
2018	3	0.000442591	0.000442493	44.17213031	99803.58795	0.5	0.999557507	99825.67401	7396927.164	74.09844449
2018	4	0.000406283	0.000406201	40.53132159	99761.23622	0.5	0.999593799	99781.50188	7297123.576	73.13102568
2018	5	0.000385549	0.000385475	38.4476314	99721.74674	0.5	0.999614525	99740.97056	7197362.34	72.16054044
2018	6	0.00037703	0.000376959	37.58371994	99683.73107	0.5	0.999623041	99702.52293	7097640.593	71.18817443
2018	7	0.000377818	0.000377746	37.64804675	99646.11519	0.5	0.999622254	99664.93921	6997956.862	70.21483099
2018	8	0.000385319	0.000385245	38.38090565	99608.10071	0.5	0.999614755	99627.29116	6898310.747	69.24117545
2018	9	0.000397061	0.000396982	39.53499678	99569.14276	0.5	0.999603018	99588.91026	6798702.646	68.26766784
2018	10	0.000410572	0.000410488	40.86381821	99528.94335	0.5	0.999589512	99549.37526	6699133.503	67.29458107
2018	11	0.0004234	0.0004231	42.12293944	99487.44997	0.5	0.99957669	99508.51144	6599604.56	66.3220107
2018	12	0.000433246	0.000433153	43.08412898	99444.84644	0.5	0.999566847	99466.3885	6500117.11	65.34988561
2018	13	0.000438202	0.000438106	43.55797371	99401.52539	0.5	0.999561894	99423.30437	6400672.264	64.37798768
2018	14	0.000436979	0.000436884	43.41739914	99358.0377	0.5	0.999563116	99379.7464	6301270.738	63.40598529
2018	15	0.000429076	0.000428984	42.61373316	99315.02213	0.5	0.999571016	99336.329	6201912.701	62.43347991
2018	16	0.000414809	0.000414723	41.17936288	99273.12559	0.5	0.999585277	99293.71527	6102597.678	61.4600598
2018	17	0.000395189	0.000395111	39.21575768	99232.92802	0.5	0.999604889	99252.5359	6003324.553	60.48535182
2018	18	0.000371698	0.000371629	36.8705485	99194.88487	0.5	0.999628371	99213.32015	5904091.625	59.50906205
2018	19	0.000346012	0.000345952	34.31033693	99159.29443	0.5	0.999654048	99176.4496	5804896.74	58.53099968
2018	20	0.000319754	0.000319703	31.69602703	99126.29125	0.5	0.999680297	99142.13926	5705737.446	57.5510826
2018	21	0.000294314	0.000294271	29.16529486	99095.86059	0.5	0.999705729	99110.44323	5606611.154	56.56932783
2018	22	0.000270762	0.000270725	26.82376468	99067.86606	0.5	0.999729275	99081.27794	5507515.294	55.58583224
2018	23	0.000249832	0.000249801	24.74390042	99042.08222	0.5	0.999750199	99054.45417	5408447.428	54.60074938
2018	24	0.00023197	0.000231943	22.96923655	99018.22566	0.5	0.999768057	99029.71027	5309405.345	53.61426718
2018	25	0.000217396	0.000217373	21.52134597	98995.98036	0.5	0.999782627	99006.74104	5210387.12	52.62658952
2018	26	0.000206188	0.000206167	20.4074588	98975.01596	0.5	0.999793833	98985.21969	5111391.139	51.63792287
2018	27	0.000198347	0.000198327	19.62742526	98954.99852	0.5	0.999801673	98964.81223	5012416.123	50.64846798
2018	28	0.000193858	0.000193839	19.17943669	98935.59509	0.5	0.999806161	98945.18481	4913461.125	49.65841576
2018	29	0.000192732	0.000192714	19.06440471	98916.47317	0.5	0.999807286	98926.00537	4814525.53	48.66794643
2018	30	0.000195043	0.000195024	19.28918306	98897.29637	0.5	0.999804976	98906.94097	4715609.057	47.67723085
2018	31	0.000200944	0.000200924	19.86889592	98877.71733	0.5	0.999799076	98887.65178	4616711.76	46.68643331
2018	32	0.000210694	0.000210671	20.82862401	98875.36857	0.5	0.999789329	98867.78289	4517834.043	45.69571514
2018	33	0.000224662	0.000224636	22.20462176	98835.85195	0.5	0.999775364	98846.95426	4418976.674	44.70523859
2018	34	0.000243341	0.000243311	24.04514377	98812.72707	0.5	0.999756689	98824.74964	4320140.822	43.71517093
2018	35	0.00026735	0.000267315	26.41086613	98787.49906	0.5	0.999732685	98800.7045	4221328.095	42.72568821
2018	36	0.000297438	0.000297393	29.37481293	98759.60622	0.5	0.999702607	98774.29363	4122540.596	41.73697877
2018	37	0.00033447	0.000334414	33.02165501	98728.40799	0.5	0.999665586	98744.91882	4023780.99	40.74924602
2018	38	0.000379421	0.000379349	37.44624837	98693.17404	0.5	0.999620651	98711.89716	3925052.582	39.76271042
2018	39	0.000433535	0.000433256	42.75133743	98653.07525	0.5	0.999566744	98674.45091	3826359.408	38.77761034
2018	40	0.000497372	0.000497249	49.04446832	98607.17734	0.5	0.999502751	98631.69958	3727706.333	37.79420155
2018	41	0.000572621	0.000572457	56.43434381	98554.43794	0.5	0.999427543	98582.65511	3629099.155	36.81275526
2018	42	0.000660215	0.000659997	65.02698845	98493.70728	0.5	0.999340003	98526.22077	3530544.718	35.83355466
2018	43	0.000761224	0.000760935	74.92250466	98423.73252	0.5	0.999239065	98461.19379	3432051.01	34.85689009
2018	44	0.000876656	0.000876272	86.21311092	98343.16469	0.5	0.999123728	98386.27125	3333627.278	33.88305335
2018	45	0.001007452	0.001006945	98.98277399	98250.56675	0.5	0.999893055	98300.05813	3235284.113	32.91233163
2018	46	0.001154524	0.001153858	113.3100984	98144.42031	0.5	0.998846142	98201.07536	3137033.546	31.94500197
2018	47	0.001318807	0.001317938	129.2735495	98023.12849	0.5	0.998682062	98087.76526	3038889.126	30.98132696
2018	48	0.001501349	0.001500223	146.9596049	97885.01191	0.5	0.998499777	97958.49171	2940865.998	30.02155246
2018	49	0.001703427	0.001701977	166.47972931	97788.29562	0.5	0.998298023	97811.53211	2842980.986	29.06590792
2018	50	0.001926661	0.001924807	187.9479106	97551.08518	0.5	0.998075193	97645.05913	2745252.69	28.11460932
2018	51	0.002173153	0.002170794	211.5593553	97351.33155	0.5	0.997829206	97457.11122	2647701.605	27.16786463
2018	52	0.002445592	0.002442605	237.5324527	97126.78564	0.5	0.997557395	97245.55187	2550350.273	26.22588102
2018	53	0.002747436	0.002743577	266.1490143	96874.94491	0.5	0.997256423	97008.01942	2453223.488	25.28887305
2018	54	0.003082516	0.003077772	297.7494415	96592.99568	0.5	0.996922228	96741.8704	2356348.543	24.35707035
2018	55	0.003455924	0.003449963	332.7286167	96277.75665	0.5	0.996550037	96444.12096	2259755.547	23.43072366
2018	56	0.003873044	0.003865558	371.5214676	95925.63026	0.5	0.996134442	96111.39234	2163477.79	22.51010767
2018	57	0.004339833	0.004330436	414.5954079	95532.57047	0.5	0.995669564	95739.86818	2067552.16	21.59551919
2018	58	0.004862461	0.004850668	462.3912821	95094.07713	0.5	0.995149332	95325.27277	1972019.59	20.68726931
2018	59	0.005446909	0.005432115	513.306054	94605.22846	0.5	0.994567885	94862.88149	1876925.513	19.78566836
2018	60	0.006098426	0.006079887	573.622593	94060.76414	0.5	0.993920113	94347.57543	1782320.284	18.89100251
2018	61	0.006820863	0.00679768	637.445281	93455.2302	0.5	0.99320232	93773.95284	1688259.592	18.00350171
2018	62	0.007615095	0.007588704	706.627972	92783.19357	0.5	0.992412986	93136.50756	1594804.29	17.12329925
2018	63	0.008482301	0.008446478	780.706956	92039.52611	0.5	0.991553522	92429.87959	1502021.096	16.25038465
2018	64	0.009415217	0.009371102	858.8537445	91219.74576	0.5	0.990628898	91649.17263	1409981.57	15.38455318
2018	65	0.010405915	0.010352053	939.866229	90320.38577	0.5	0.989647947	90790.31889	1318761.824	14.52535733
2018	66	0.01144196	0.011376873	1022.212727	8939.34040	0.5	0.988623127	89850.45266	1228441.439	13.6720733
2018	67	0.012508186	0.012430445	1104.174502	88276.14818	0.5	0.987569555	88828.23543	1139102.094	12.8236488
2018	68	0.01358851	0.01349681	1183.994942	87132.06346	0.5	0.98050319	87724.06093	1050825.946	11.97876541
2018	69	0.014668599	0.014561798	1260.178976	85909.9765	0.5	0.985438202	86540.06598	96369.8828	11.13581174
2018	70	0.015739161	0.015616268	1331.753548	84614.01023	0.5</				

Table 17: Combined Sex Life Table in 2019
 National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2019	0	0.000946563	0.000945799	94.57989863	99919.29779	0.1467298	0.999054201	100000	7535405.708	75.35405708
2019	1	0.000810492	0.000810164	80.93976289	99864.95022	0.5	0.999189836	99905.4201	7435486.409	74.42525543
2019	2	0.000701826	0.000701579	70.03480233	99789.46294	0.5	0.999298421	99824.48034	7335621.459	73.48519556
2019	3	0.000623676	0.000623482	62.195073781	99723.348	0.5	0.999376518	99754.44554	7235831.996	72.53643642
2019	4	0.000572514	0.00057235	57.05884645	99663.72104	0.5	0.99942765	99692.25046	7136108.648	71.58137784
2019	5	0.000543296	0.000543149	54.11671931	99608.13326	0.5	0.999456851	99635.19162	7036444.927	70.62208456
2019	6	0.000531291	0.000531115	52.89247409	99554.62866	0.5	0.99946885	99581.0749	6936836.794	69.66019197
2019	7	0.000532401	0.00053226	52.97482162	99501.69501	0.5	0.99946774	99528.18242	6837282.165	68.69694592
2019	8	0.000542972	0.000542825	53.99760171	99448.2088	0.5	0.999457175	99475.2076	6737780.47	67.73326372
2019	9	0.000559518	0.000559361	55.61237596	99393.40381	0.5	0.999440639	99421.21	6638332.262	66.76977942
2019	10	0.000578557	0.00057839	57.4720822	99336.86158	0.5	0.99942161	99365.59762	6538938.858	65.80686892
2019	11	0.000596633	0.000596455	59.23284107	99278.50912	0.5	0.999403545	99308.12554	6439601.996	64.84466363
2019	12	0.000610509	0.000610323	60.57383954	99218.60578	0.5	0.999389677	99248.8927	6340323.487	63.88306524
2019	13	0.000617492	0.000617302	61.22912168	99157.7043	0.5	0.999382698	99188.31886	6241104.881	62.92177298
2019	14	0.000615769	0.000615579	61.02059095	99096.57944	0.5	0.999384421	99127.08974	6141947.177	61.96032985
2019	15	0.000604633	0.000604445	59.88047567	99036.12891	0.5	0.99935955	99066.06915	6042850.598	60.99818686
2019	16	0.000584527	0.000584357	57.8549212	98977.26121	0.5	0.999415643	99006.18867	5943814.469	60.0347771
2019	17	0.00055688	0.000556725	55.08702619	98920.79024	0.5	0.999443275	98948.33375	584837.207	59.06958698
2019	18	0.000523778	0.000523641	51.78454691	98867.35445	0.5	0.999476359	98893.24672	5745916.417	58.10221231
2019	19	0.000487583	0.000487464	48.18166446	98817.37135	0.5	0.999512536	98841.46218	5647049.063	57.13239099
2019	20	0.000450581	0.000450458	44.50435315	98771.02834	0.5	0.99954952	98793.28051	5548231.691	56.16001071
2019	21	0.000414732	0.000414646	40.94581106	98728.30325	0.5	0.999585354	98748.77616	5449460.663	55.1850957
2019	22	0.000381543	0.000381471	37.65413122	98689.00328	0.5	0.999618529	98707.83035	5350732.36	54.20778008
2019	23	0.000352051	0.000351989	34.73080164	98652.81082	0.5	0.999648011	98670.17622	5252043.356	53.22827584
2019	24	0.00032688	0.000326827	32.23668697	98619.32707	0.5	0.999673173	98635.44542	5153390.546	52.24684214
2019	25	0.000306344	0.000306297	30.2018361	98588.10781	0.5	0.999693703	98603.20873	5054771.219	51.26375991
2019	26	0.00029055	0.000290507	28.6361885	98558.6888	0.5	0.999709493	98573.00689	4956183.111	50.2931344
2019	27	0.0002795	0.000279461	27.53934929	98530.60103	0.5	0.999720539	98544.37071	4857624.422	49.29377891
2019	28	0.000273175	0.000273137	26.90861493	98503.37705	0.5	0.999726863	98516.83136	4759093.821	48.3074187
2019	29	0.000271589	0.000271552	26.74511062	98476.55019	0.5	0.999728448	98489.92274	4660590.444	47.32048025
2019	30	0.000274844	0.000274806	27.05830153	98449.64848	0.5	0.999725194	98463.17763	4562113.894	46.33319789
2019	31	0.00028316	0.000283112	27.86924803	98422.1847	0.5	0.99971688	98436.11933	4463664.245	45.3457966
2019	32	0.000296899	0.000296855	29.21295733	98393.6436	0.5	0.999703145	98408.25008	4365242.061	44.35849694
2019	33	0.000316582	0.000316532	31.1400743	98363.46709	0.5	0.999683468	98379.03712	4266848.417	43.37152041
2019	34	0.000342903	0.000342844	33.71801997	98331.03804	0.5	0.999657156	98347.89705	4168484.95	42.3850949
2019	35	0.000376736	0.000376665	37.03155571	98295.66325	0.5	0.999623335	98314.17903	4070153.912	41.39945989
2019	36	0.000419134	0.000419046	41.18264583	98256.55615	0.5	0.999580954	98277.14747	3971858.249	40.41487111
2019	37	0.000471318	0.000471207	46.28942972	98212.82011	0.5	0.999528793	98235.96483	3873601.692	39.43160429
2019	38	0.000534661	0.000534518	52.48411564	98163.43334	0.5	0.999465482	98189.6754	3775388.872	38.4495777
2019	39	0.000610655	0.000610469	59.906968928	98107.23644	0.5	0.999389531	98137.19128	3677225.439	37.47025354
2019	40	0.000700872	0.000700626	68.71549902	98042.92384	0.5	0.999299374	98077.28159	3579118.203	36.49283651
2019	41	0.000806908	0.000806583	79.05202958	97969.04008	0.5	0.999193417	98008.56609	3481075.279	35.51807171
2019	42	0.000903041	0.0009029908	91.0654691	97883.98133	0.5	0.999070092	97929.51406	3383106.239	34.54633949
2019	43	0.001072679	0.001072104	104.8929508	97786.00212	0.5	0.998927894	97838.4486	3285222.257	33.57802893
2019	44	0.001235339	0.001235476	120.659526	97673.22588	0.5	0.998765424	97733.55564	3187436.255	32.61353006
2019	45	0.001419651	0.001418644	138.4779219	97543.65716	0.5	0.998581356	97612.89612	3089763.029	31.65322567
2019	46	0.001626897	0.001625574	158.4519062	97395.19224	0.5	0.998374426	97474.4182	2992219.372	30.69748379
2019	47	0.001858395	0.00185667	180.683628	97225.62448	0.5	0.99814333	97315.96629	2894824.18	29.74665196
2019	48	0.002115625	0.00211339	205.2846958	97032.64031	0.5	0.997886161	97135.28266	2797598.555	28.80105435
2019	49	0.002400382	0.002397505	232.390108	96813.80291	0.5	0.997602495	96929.99797	2700565.915	27.860099218
2019	50	0.002714953	0.002711273	262.1735832	96566.52107	0.5	0.997288727	96697.60786	2603752.112	26.92674793
2019	51	0.003062297	0.003057615	294.8624471	96288.00305	0.5	0.996942385	96435.43428	2507185.591	25.99859284
2019	52	0.003446203	0.003404275	330.7500322	95975.19681	0.5	0.996559725	96140.57183	2410897.588	25.07679684
2019	53	0.00387142	0.003863941	370.2034972	95624.72005	0.5	0.996136059	95809.8218	2314922.391	24.16163967
2019	54	0.004434724	0.004343311	413.6649799	95232.78581	0.5	0.9956565689	95439.6183	2219297.671	23.25342149
2019	55	0.004869912	0.004858083	461.6439747	94795.13133	0.5	0.995141917	95025.95332	2124064.885	22.35247121
2019	56	0.005457696	0.005442843	514.6987349	94306.95998	0.5	0.994557157	94564.30934	209269.754	21.45915058
2019	57	0.006115472	0.006107465	573.4044262	93762.9084	0.5	0.993903171	94049.61061	1934962.794	20.57385226
2019	58	0.006851933	0.006828539	638.3058996	93157.05323	0.5	0.993171461	94376.20618	1841199.886	19.69698986
2019	59	0.007675507	0.007646163	709.8536783	92482.97344	0.5	0.992355387	92837.90028	1748042.832	18.82897854
2019	60	0.008593591	0.008556824	788.3235098	91733.88485	0.5	0.991443176	92128.0466	1655559.859	17.97020473
2019	61	0.009611612	0.009565642	873.7230645	90902.86156	0.5	0.990434358	91339.7231	1563825.974	17.1209844
2019	62	0.010731945	0.010674665	965.6942852	89983.15289	0.5	0.998925353	90466.00003	1472923.113	16.28151031
2019	63	0.011952827	0.011881816	1063.426167	88968.59266	0.5	0.988118184	89500.30575	1382939.96	15.45179034
2019	64	0.013267445	0.013180013	1165.591913	87854.07998	0.5	0.986819987	88436.87958	1293971.367	14.631581
2019	65	0.014663485	0.014556759	1270.386986	86636.08689	0.5	0.985443241	8721.28039	1206117.287	13.82032304
2019	66	0.016123428	0.015994485	1375.540005	8513.31234	0.5	0.984005515	86000.8934	1119481.2	13.01708803
2019	67	0.017625899	0.01747192	1478.567422	83886.06968	0.5	0.98252808	84625.3534	1034168.077	12.22054662
2019	68	0.019148237	0.018966648	1577.01583	82358.27806	0.5	0.98103352	83146.78597	950282.0071	11.42896861
2019	69	0.020670243	0.020458799	1668.819496	80735.3604	0.5	0.979541201	81569.77014	867923.729	10.64026204
2019	70	0.022178825	0.021935572	1752.673072	79024.61411	0.5	0.978064428			

Table 18: Combined Sex Life Table in 2020
 National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2020	0	0.001063668	0.001062703	106.2702812	99909.28198	0.1463463	0.998937297	100000	7470402.495	74.70402495
2020	1	0.000910763	0.000910348	90.938096868	99848.26067	0.5	0.999089652	99893.72972	7370493.211	73.78334188
2020	2	0.000788653	0.000788342	78.67870633	99763.45227	0.5	0.999211658	99802.79162	7270644.951	72.85011604
2020	3	0.000700835	0.000700589	69.8656462	99689.18009	0.5	0.999299411	99724.11292	7170881.498	71.90719766
2020	4	0.000643343	0.000643136	64.09122081	99622.20166	0.5	0.999356864	99654.24727	7071192.318	70.95725985
2020	5	0.000610511	0.000610324	60.78228761	99559.7649	0.5	0.999389676	99590.15605	6971570.117	70.0026026
2020	6	0.00059702	0.000596842	59.40330303	99499.67211	0.5	0.999403158	99529.37376	6872010.352	69.04504763
2020	7	0.000598268	0.000598089	59.49187262	99440.22452	0.5	0.999401911	99469.97046	6772510.68	68.08598262
2020	8	0.000610146	0.00060996	60.63643415	99380.16036	0.5	0.99939004	99410.47859	6673070.455	67.12642923
2020	9	0.000628739	0.000628541	62.44549026	99318.6194	0.5	0.999371459	99349.84214	6573690.295	66.16709351
2020	10	0.000650134	0.000649923	64.52915643	99255.13207	0.5	0.999350077	99287.39665	6474371.675	65.20839395
2020	11	0.000670446	0.000670221	66.5012868	99189.61685	0.5	0.999329779	99222.86775	6375116.543	64.25047677
2020	12	0.000686039	0.000685803	68.0017609	99122.36533	0.5	0.999314197	99156.36621	6275926.927	63.29323236
2020	13	0.000693886	0.000693645	68.73217642	99053.99836	0.5	0.999306355	99088.36445	6176804.561	62.33632572
2020	14	0.000691949	0.00069171	68.49286687	98985.38584	0.5	0.99930829	99019.63227	6077750.563	61.37924797
2020	15	0.000679435	0.000679205	67.20806493	98917.53537	0.5	0.999320795	98951.1394	5978765.177	60.4213879
2020	16	0.000656843	0.000656627	64.92986643	98851.46461	0.5	0.999343373	98883.93134	5879847.642	59.46211444
2020	17	0.000625775	0.000625579	61.81912695	98788.09191	0.5	0.999374421	98819.00147	5780996.175	58.500856
2020	18	0.000585878	0.000588405	58.10917211	98728.12776	0.5	0.999411595	98757.18235	5682208.083	57.53716285
2020	19	0.000547905	0.000547755	54.06287483	98672.04174	0.5	0.999452245	98699.07317	5583479.956	56.57074353
2020	20	0.000506325	0.000506197	49.93380101	98620.0434	0.5	0.999493803	98645.0103	5484807.914	55.60147338
2020	21	0.000466041	0.000465933	45.93866439	98572.10717	0.5	0.999534067	98595.0765	5386187.87	54.6293797
2020	22	0.000428746	0.000428654	42.24352263	98528.01607	0.5	0.999571346	98549.13783	5287615.763	53.6546121
2020	23	0.000395605	0.000395527	38.96212129	98487.41325	0.5	0.999604473	98506.89431	5189087.747	52.67740683
2020	24	0.00036732	0.000367253	36.16262511	98449.85088	0.5	0.999632747	98467.93219	5090600.334	51.69805256
2020	25	0.000344243	0.000344184	33.87863329	98414.83025	0.5	0.999655816	98431.76956	4992150.483	50.7168621
2020	26	0.000326495	0.000326442	32.12119599	98381.83033	0.5	0.999673558	98397.89093	4893735.653	49.73415189
2020	27	0.000314079	0.00031403	30.88978321	98350.32484	0.5	0.99968597	98365.76974	4795353.822	48.75022922
2020	28	0.000306971	0.000306923	30.18128194	98319.78931	0.5	0.999693077	98334.87995	4697003.498	47.76538599
2020	29	0.000305188	0.000305142	29.99688113	98289.70023	0.5	0.999694858	98304.69867	4598683.708	46.7798973
2020	30	0.000308847	0.000308799	30.34712518	98259.52823	0.5	0.999691201	98274.70179	4500394.008	45.79402355
2020	31	0.000318192	0.000318141	31.25555998	98228.72688	0.5	0.999681859	98244.35466	4402134.48	44.80801462
2020	32	0.000333633	0.000333574	32.76136399	98196.71842	0.5	0.999666426	98213.0991	4303905.753	43.8221153
2020	33	0.000355748	0.000355685	34.92123662	98162.87712	0.5	0.999644315	98180.33774	4205709.035	42.83657127
2020	34	0.000385326	0.000385251	37.81066511	98126.51117	0.5	0.999614749	98145.4165	4107546.157	41.85163509
2020	35	0.000423345	0.000423255	41.5245446	98086.84357	0.5	0.999576745	98107.60584	4009419.646	40.86757201
2020	36	0.000470987	0.000470876	47.17700757	98042.99279	0.5	0.999529124	98066.08129	3911332.803	39.88466502
2020	37	0.000529627	0.000529487	51.90025003	97993.95416	0.5	0.999470513	98019.90429	3813289.81	38.90321907
2020	38	0.000600807	0.000600626	58.84214275	97938.58296	0.5	0.999399374	97968.00404	3715295.856	37.92356384
2020	39	0.000686203	0.000685968	67.16250648	97875.58064	0.5	0.999314032	97909.16189	3617357.273	36.94605492
2020	40	0.000787581	0.000787271	77.02812051	97803.48533	0.5	0.999212729	97841.99939	3519481.692	35.97107289
2020	41	0.000906736	0.000906325	88.60681324	97720.66786	0.5	0.999093675	97764.97127	3421678.207	34.99902023
2020	42	0.001045439	0.001044893	102.0613138	97625.3338	0.5	0.998955107	97676.36445	3323957.539	34.03031591
2020	43	0.001205386	0.00120466	117.543853	97515.53121	0.5	0.99879534	97574.30314	3226332.205	33.06538813
2020	44	0.00138817	0.001387207	135.1926982	97389.16294	0.5	0.998612793	97456.75929	3128816.674	32.10466567
2020	45	0.001595284	0.001594013	155.1318031	97244.00696	0.5	0.998405987	97321.56659	3031427.511	31.14856878
2020	46	0.00182817	0.00182865	177.4744895	97077.69754	0.5	0.9981735	97166.43479	2934183.51	30.19750099
2020	47	0.002088308	0.00208613	202.3315694	96887.79451	0.5	0.99791387	96988.9603	2837105.813	29.25184273
2020	48	0.002377362	0.002377459	229.8236277	96671.71691	0.5	0.997625461	96786.62873	2740218.018	28.31194819
2020	49	0.002697347	0.002693714	260.0964577	96426.75687	0.5	0.997306286	96556.8051	2643546.301	27.37814594
2020	50	0.003050836	0.003046189	293.3380029	96150.03964	0.5	0.996953811	96296.70864	2547119.544	26.45074354
2020	51	0.003441152	0.003435241	329.7974718	95838.47328	0.5	0.996546759	96003.37064	2450969.505	25.53003596
2020	52	0.003872553	0.003865069	369.7850153	95488.68342	0.5	0.996134931	95673.57592	2355131.032	24.61631656
2020	53	0.004450377	0.004430934	413.7074952	95096.93716	0.5	0.995659066	95303.79091	2259642.348	23.70988947
2020	54	0.004881112	0.004869229	462.041501	94659.06266	0.5	0.995130771	94890.08341	2164545.411	22.81108134
2020	55	0.005472398	0.005457465	515.3377406	94170.37304	0.5	0.994542535	94428.04191	2069886.348	21.92025066
2020	56	0.0061329	0.006114151	574.196467	93625.60594	0.5	0.993885849	93912.70417	1975715.975	21.03779241
2020	57	0.006872053	0.006848521	639.2307431	93018.89233	0.5	0.993151479	93338.5077	1882090.369	20.16413606
2020	58	0.007699626	0.007670098	711.0125059	92437.77071	0.5	0.992329902	92699.27696	1789071.477	19.29973497
2020	59	0.008625089	0.008588052	790.000335	91593.26444	0.5	0.991411948	91988.26446	1696727.706	18.44504531
2020	60	0.009656755	0.009610353	876.447474	90760.04068	0.5	0.990389647	91198.26442	1605134.442	17.6004933
2020	61	0.010800721	0.010742707	970.3008091	89836.66654	0.5	0.989257293	90321.81695	1514374.401	16.76642978
2020	62	0.012050968	0.011987376	1071.090193	88815.97104	0.5	0.988012624	89351.51614	1424537.735	15.94307289
2020	63	0.013431581	0.0133411979	1177.83561	87691.50814	0.5	0.986658021	88280.42595	1335721.764	15.13044086
2020	64	0.014908839	0.014798524	1288.989817	86458.09543	0.5	0.985201476	87102.59034	1248030.255	14.32827945
2020	65	0.016477591	0.016342945	1402.446965	85112.37704	0.5	0.983657055	85813.60052	1161572.16	13.53599142
2020	66	0.018118152	0.017955492	1516.537491	83653.33166	0.5	0.982044058	84411.15356	1076459.783	12.75257756
2020	67	0.019806503	0.019612278	1625.76976	82082.62488	0.5	0.980387722	82895.50976	992806.4513	11.97660107
2020	68	0.021517178	0.021288148	1730.082224	80404.69889	0.5	0.978711852	81269.74	910723.8264	11.20618605
2020	69	0.023227478	0.022960819	1826.295691	78626.50993	0.5	0.977039181	79539.65778	830319.1275	10.43905834
2020	70	0.024922698	0.02461595	1912.988217	76756.86798	0.5				

Table 19: Combined Sex Life Table in 2021
 National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2021	0	0.000953152	0.000952377	95.23772456	99918.73593	0.1467239	0.999047623	100000	7531691.956	75.31691956
2021	1	0.000816134	0.000815801	81.50241065	99864.01107	0.5	0.999184199	99904.76228	7431773.22	74.38857819
2021	2	0.000706711	0.000706461	70.52127372	99787.99923	0.5	0.999293539	99823.25986	7331909.209	73.44890578
2021	3	0.000628018	0.000626782	62.62680044	99721.42519	0.5	0.99937218	99752.73859	7232121.209	72.5004778
2021	4	0.000576499	0.000576333	57.45468079	99661.38445	0.5	0.999423667	99690.11179	7132399.784	71.54570956
2021	5	0.000547078	0.000546928	54.49193161	99605.41114	0.5	0.999453072	99632.65711	7032738.4	70.58667914
2021	6	0.000534989	0.000534846	53.25899002	9951.553568	0.5	0.999465154	99578.16518	6933132.989	69.62503252
2021	7	0.000536107	0.000535964	53.34171971	99498.23532	0.5	0.999464036	99524.90618	6833581.453	68.66202356
2021	8	0.000546752	0.000546602	54.37137997	99444.37877	0.5	0.999453398	99471.56446	6734083.218	67.69857551
2021	9	0.000563413	0.000563254	55.99711703	99389.19452	0.5	0.999436746	99417.19308	6634638.839	66.73532649
2021	10	0.000582585	0.000582415	57.86945998	99332.26123	0.5	0.999417585	99361.19596	6535249.644	65.77265482
2021	11	0.000600786	0.000600606	59.64214927	99273.50543	0.5	0.999399394	99303.3265	6435917.383	64.81069275
2021	12	0.000614759	0.00061457	60.992158	99213.18827	0.5	0.999385453	99423.68435	6336643.878	63.84934133
2021	13	0.000621791	0.000621597	61.65170198	99151.86634	0.5	0.999378403	99182.6922	6237430.689	62.88829786
2021	14	0.000620055	0.000619863	61.44146831	99090.31976	0.5	0.999380137	99121.04049	6138278.823	61.92710238
2021	15	0.000608841	0.000608656	60.29323232	99029.45241	0.5	0.999391344	99059.59902	6039188.503	60.96520239
2021	16	0.000588596	0.000588423	58.25347458	98970.17905	0.5	0.999411577	98999.30579	5940159.051	60.00202732
2021	17	0.000560757	0.000560599	55.46629246	98913.31917	0.5	0.999439401	98941.05232	5841188.872	59.0370603
2021	18	0.000527424	0.000527285	52.14087996	98859.51558	0.5	0.999472715	98885.58602	5742275.553	58.06989455
2021	19	0.000490977	0.000490856	48.51303506	98809.18863	0.5	0.999509144	98833.44514	563416.037	57.1002663
2021	20	0.000453717	0.000453615	44.81028663	98762.52697	0.5	0.999546385	98784.93211	5544606.848	56.12806255
2021	21	0.000417619	0.000417532	41.22715811	98719.50824	0.5	0.999582468	98740.12182	5445844.321	55.1533077
2021	22	0.000384199	0.000384125	37.9127554	98679.93829	0.5	0.999615875	98698.89466	5347124.813	54.17613674
2021	23	0.000354501	0.000354439	34.96925789	98643.49728	0.5	0.999645561	98660.98191	5248444.875	53.19676303
2021	24	0.000329155	0.000329101	32.45794232	98609.73836	0.5	0.999670899	98626.01265	5149801.378	52.21544742
2021	25	0.000308476	0.000308428	30.4090583	98578.35018	0.5	0.999691572	98593.55471	5051191.594	51.23247264
2021	26	0.000292572	0.000292529	28.83260816	98548.72935	0.5	0.999707471	98563.14565	4952613.244	50.2481248
2021	27	0.000281446	0.000281406	27.7281909	98520.44895	0.5	0.999718594	98534.31304	4854064.514	49.26268185
2021	28	0.000275076	0.000275038	27.09307938	98493.03831	0.5	0.999724962	98506.58485	4755544.065	48.27640784
2021	29	0.000273479	0.000273442	26.92840315	98466.02757	0.5	0.999726558	98479.49177	4657051.027	47.2895518
2021	30	0.000276757	0.000276719	27.24368865	98438.94152	0.5	0.999723281	98452.56337	4558585	46.30234951
2021	31	0.000285131	0.000285091	28.06013676	98411.28961	0.5	0.999714909	98425.31968	4460146.058	45.3150274
2021	32	0.000298966	0.000298921	29.41299034	98382.55305	0.5	0.999701079	98397.25954	4361734.768	44.32780739
2021	33	0.000318785	0.000318735	31.35323613	98352.16993	0.5	0.999681265	98367.84655	4263352.215	43.34091235
2021	34	0.00034529	0.000345253	33.94875057	98319.51894	0.5	0.999654757	98336.49332	4165000.045	42.35457158
2021	35	0.000379359	0.000379287	37.28486727	98283.90213	0.5	0.999620713	98302.54457	4066680.526	41.36902605
2021	36	0.000422051	0.000421962	41.46423776	98244.52758	0.5	0.999578038	98265.2597	3968396.624	40.38453301
2021	37	0.000474598	0.000474486	46.60579554	98200.49256	0.5	0.999525514	98223.79546	3870152.097	39.40136989
2021	38	0.000538382	0.000538327	52.84263413	98150.76835	0.5	0.999461763	98177.18967	3771951.604	38.4198368
2021	39	0.000614906	0.000614717	60.31869135	98094.18769	0.5	0.999385283	98124.34703	3673800.836	37.44025766
2021	40	0.00070575	0.000705051	69.18430237	98029.43619	0.5	0.999294499	98064.02834	3575706.648	36.46297943
2021	41	0.000812525	0.000812195	79.59093503	97955.04857	0.5	0.999187805	97994.84404	3477677.212	35.48836927
2021	42	0.000936817	0.000936378	91.68571701	97869.41024	0.5	0.999063622	97915.2531	3379722.163	34.51680975
2021	43	0.001080145	0.001079562	105.6066417	97770.76406	0.5	0.9998920438	97823.56739	3281852.753	33.54869221
2021	44	0.001243938	0.001243165	121.4795168	97657.22099	0.5	0.998756835	97717.96074	3184081.989	32.58440889
2021	45	0.001429533	0.001428512	139.4177166	97526.77237	0.5	0.998571488	97596.48123	3086424.768	31.62434474
2021	46	0.001638221	0.001636888	159.5255651	97377.30073	0.5	0.99836312	97457.06351	2988897.996	30.66886984
2021	47	0.001871331	0.001869582	181.9057211	97206.58508	0.5	0.998130418	97297.53795	2891520.695	29.71833364
2021	48	0.002130352	0.002128085	206.6703254	97012.29706	0.5	0.997871915	97115.63222	2794314.11	28.77306203
2021	49	0.002417091	0.002414173	233.9550168	96791.98439	0.5	0.997585827	96908.9619	2697301.813	27.83335782
2021	50	0.002733852	0.00273012	263.9343548	96543.0397	0.5	0.99726988	96675.00688	2600509.828	26.89950497
2021	51	0.003086313	0.003078866	296.8367911	96262.65413	0.5	0.996921134	96411.07253	2503966.789	25.9717761
2021	52	0.003470192	0.003464181	332.9571319	95947.57717	0.5	0.996535819	96114.23574	2407704.135	25.05044249
2021	53	0.003889839	0.003890785	372.664381	95594.94641	0.5	0.996109215	95781.2786	2311756.377	24.13578531
2021	54	0.004373961	0.004364416	416.4028655	95200.41279	0.5	0.995635584	95408.61422	2216161.431	23.22810628
2021	55	0.004903811	0.004891817	464.6845166	94759.8691	0.5	0.995108183	94992.21136	2120961.018	22.32773601
2021	56	0.005495687	0.005480627	518.0700963	94689.49179	0.5	0.994519373	94527.52684	2026201.149	21.4350382
2021	57	0.006158041	0.006139139	577.1370796	93720.88821	0.5	0.993860861	94009.45674	1931932.657	20.55040763
2021	58	0.006899629	0.006875908	642.432053	93111.10364	0.5	0.993124094	94342.31967	1838211.769	19.67426021
2021	59	0.007728935	0.007699182	714.4062244	92432.68485	0.5	0.992300818	92789.88761	1745100.666	18.80701346
2021	60	0.00865341	0.008616131	793.3344081	91678.81418	0.5	0.991383869	92075.48139	1652667.981	17.9490561
2021	61	0.009678518	0.009631907	879.2211124	90842.55362	0.5	0.990368093	91282.14693	1560989.167	17.10070609
2021	62	0.01080665	0.010748571	971.7023105	89917.07471	0.5	0.989251429	90402.92587	1470146.63	16.26215763
2021	63	0.012036029	0.011964029	1069.957796	88896.24466	0.5	0.988035971	89431.22356	1380229.556	15.43341912
2021	64	0.01359799	0.013271149	1172.6555	87774.93801	0.5	0.986728851	88361.26576	1291333.311	14.61424641
2021	65	0.014765556	0.014657345	1277.9535	86549.63351	0.5	0.985342655	87188.61026	1203558.373	13.80407796
2021	66	0.016235662	0.016104925	1383.584655	85218.86443	0.5	0.983895075	85910.65676	1117008.74	13.00198115
2021	67	0.0174748592	0.017592471	1487.04005	83783.55208	0.5	0.982407529	84527.0721	1031789.875	12.20662031
2021	68	0.019281526	0.019097413	1585.849748	82247.10718	0.5	0.980902587	83040.03205	948006.323	11.41625671
2021	69	0.020814126	0.020599744	1677.935267	80615.21467	0.5	0.979400256	81454.18231	865759.2158	10.6287776
2021	70	0.02233321	0.022086577	1761.984262	78895.25491	0				

Table 20: Combined Sex Life Table in 2022
 National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2022	0	0.000681111	0.000680715	68.07152917	99941.93833	0.1470492	0.999319285	100000	7690908.857	76.90908857
2022	1	0.000583199	0.000583029	58.2632571	99902.79684	0.5	0.999416971	99931.92847	7590966.919	75.96137726
2022	2	0.000505007	0.00050488	50.42417922	99848.45312	0.5	0.99949512	99873.66521	7491064.122	75.00539913
2022	3	0.000448774	0.000448673	44.78799685	99800.84704	0.5	0.99951327	99823.24103	7391215.669	74.04303439
2022	4	0.000411959	0.000411874	41.09618275	99757.90495	0.5	0.999588126	99778.45304	7291414.822	73.07604598
2022	5	0.000390935	0.000390859	38.98323778	99717.86524	0.5	0.999609141	99737.35685	7191656.917	72.10595051
2022	6	0.000382297	0.000382244	38.10708835	99679.32007	0.5	0.999617776	99698.37362	7091939.052	71.13394928
2022	7	0.000383096	0.000383022	38.17210966	99641.18047	0.5	0.999616978	99660.26653	6992259.732	70.16095757
2022	8	0.000390702	0.000390626	38.91496256	99602.63694	0.5	0.999609374	99622.09442	6892618.551	69.1876495
2022	9	0.000402608	0.000402527	40.0848934	99563.13701	0.5	0.999597473	99583.17946	6793015.914	68.21449116
2022	10	0.000416308	0.000416221	41.43196382	99522.37858	0.5	0.999583779	99543.09456	6693452.777	67.24175903
2022	11	0.000429315	0.000429222	42.70834231	99480.30843	0.5	0.999570778	99501.6626	6593930.399	66.26954994
2022	12	0.000432929	0.000432923	43.68262858	99437.11294	0.5	0.999560797	99458.95426	6494450.09	65.29779183
2022	13	0.0004444234	0.000444225	44.16278685	99393.19024	0.5	0.999555775	99415.27163	6395012.977	64.32626369
2022	14	0.000443084	0.000442986	44.01999127	99349.09885	0.5	0.999557014	99371.10884	6295619.787	63.35462954
2022	15	0.000435071	0.000434976	43.2049098	99305.4864	0.5	0.999565024	99327.08885	6196270.688	62.38248558
2022	16	0.000420604	0.000420515	41.75039452	99263.00874	0.5	0.999579485	99283.88394	6096965.202	61.4094147
2022	17	0.0004004071	0.00040063	39.75933517	99222.25388	0.5	0.99959937	99242.13355	5997702.193	60.43503882
2022	18	0.000376891	0.00037682	37.38141833	99183.6835	0.5	0.99962318	99202.37421	5898479.939	59.45906019
2022	19	0.000350846	0.000350785	34.78555867	99147.60001	0.5	0.999649215	99164.99279	5799296.256	58.48128551
2022	20	0.000324221	0.000324168	32.13488933	99114.13979	0.5	0.999675832	99130.20723	5700148.656	57.50163159
2022	21	0.000298426	0.000298381	29.56898988	99083.28785	0.5	0.999701619	99098.07234	5601034.516	56.52011572
2022	22	0.000274544	0.000274506	27.19494178	99054.90588	0.5	0.999725494	99068.50333	5501951.228	55.53683605
2022	23	0.000253322	0.00025329	25.08205292	99028.76531	0.5	0.99974671	99041.30841	5402896.322	54.55194816
2022	24	0.000235251	0.000235183	23.28691309	99004.57875	0.5	0.999764817	99016.22221	5303867.557	53.56564247
2022	25	0.000220433	0.000220409	21.81892894	98982.02583	0.5	0.999779591	98982.93529	5204862.978	52.57812553
2022	26	0.000209068	0.000209047	20.68957824	98960.77158	0.5	0.999709053	98971.11636	5105880.952	51.58960654
2022	27	0.000201118	0.000201098	19.89870524	98940.47743	0.5	0.999798902	98950.42679	5006920.181	50.60028889
2022	28	0.000196566	0.000196547	19.44471753	98920.80585	0.5	0.999804533	98930.52808	4907979.703	49.61036597
2022	29	0.000195425	0.000195406	19.32779778	98901.41971	0.5	0.999804594	98911.08361	4809058.898	48.62002035
2022	30	0.000197767	0.000197748	19.55562868	98881.978	0.5	0.999802252	98891.75581	4710157.478	47.62942511
2022	31	0.000203751	0.000203731	20.14329352	98862.12854	0.5	0.999796269	98872.20018	4611275.5	46.6387467
2022	32	0.000213637	0.000213614	21.11621514	98841.49878	0.5	0.999786386	98852.05689	4512413.371	45.64814849
2022	33	0.0002278	0.00022774	22.511194351	98819.6851	0.5	0.999772226	98830.94067	4413571.873	44.65779484
2022	34	0.00024674	0.00024671	24.37699316	98796.24103	0.5	0.999752329	98808.42953	4314752.187	43.66755514
2022	35	0.000271085	0.000271049	26.77526957	98770.6649	0.5	0.999728951	98784.05254	4215955.946	42.6785077
2022	36	0.000301593	0.000301547	29.77993897	98742.38727	0.5	0.999698453	98757.27727	4117185.282	41.68994322
2022	37	0.000339142	0.000339085	33.47699085	98710.75878	0.5	0.999660915	98727.49727	4018442.894	40.70236768
2022	38	0.000384721	0.000384647	37.96240567	98675.03908	0.5	0.999615353	98694.02028	3919732.135	39.71600432
2022	39	0.000439404	0.000439308	43.34037377	98634.38769	0.5	0.999560692	98656.05788	3821057.096	38.73109446
2022	40	0.000504321	0.000504193	49.71988942	98587.85756	0.5	0.999495807	98612.7175	3722422.709	37.74789706
2022	41	0.000580621	0.000580452	57.21109866	98534.39207	0.5	0.999419548	98562.99761	3623834.851	36.76668668
2022	42	0.000669438	0.000669214	65.92145417	98472.82579	0.5	0.999330786	98505.78652	3525300.459	35.78774998
2022	43	0.000771859	0.000771751	75.95236859	98401.88888	0.5	0.999228439	98439.86506	3426827.633	34.81138085
2022	44	0.000888903	0.000888508	87.39713054	98320.21413	0.5	0.999111492	98363.91269	3328425.744	33.83787462
2022	45	0.001021527	0.001021005	100.340471	98226.34514	0.5	0.998578995	98276.51556	3230105.53	32.86752193
2022	46	0.001170653	0.001169968	114.8630121	98118.74321	0.5	0.998830032	98176.17472	3131879.185	31.90060312
2022	47	0.001337231	0.001336337	131.0429783	97995.79021	0.5	0.998663663	98061.3117	3033760.442	30.93738386
2022	48	0.001522324	0.001521166	148.9681769	97855.78464	0.5	0.998478834	97930.26873	2935764.652	29.9781129
2022	49	0.001727224	0.001725734	168.7444672	97696.92832	0.5	0.998274266	97781.30055	2837908.867	29.02302231
2022	50	0.001953577	0.001951671	190.5075962	97517.30228	0.5	0.998048329	97612.55608	2740211.939	28.07233054
2022	51	0.002203513	0.002201088	214.4344677	97314.83125	0.5	0.997798192	97422.04849	2642694.636	27.12624788
2022	52	0.002479757	0.002476686	240.7527757	97087.23763	0.5	0.997523314	97207.61402	2545379.805	26.18498387
2022	53	0.002785727	0.002781853	269.7475202	96831.98748	0.5	0.997281741	96966.86124	2448292.568	25.24875546
2022	54	0.003125579	0.003120702	301.7629189	96546.23226	0.5	0.996879298	96697.11372	2351460.58	24.31779491
2022	55	0.003504204	0.003498075	337.1981936	96226.75171	0.5	0.996501925	96395.3508	2254914.348	23.39235585
2022	56	0.003927151	0.003919455	376.4956183	95869.9048	0.5	0.996080545	96058.15261	2158687.596	22.47271614
2022	57	0.004400462	0.004398081	420.1191082	95471.59744	0.5	0.995609199	95681.65699	2062817.691	21.55917609
2022	58	0.004930931	0.004918267	468.5216626	95027.27705	0.5	0.995081733	95261.53788	1967346.094	20.65205053
2022	59	0.005523004	0.005507794	522.10039	94531.96602	0.5	0.994492206	94793.01622	1872318.817	19.75165357
2022	60	0.006183622	0.006164563	581.1389823	93980.34634	0.5	0.993835437	94270.91583	1777786.851	18.85827495
2022	61	0.006916152	0.006892318	645.739707	93366.90699	0.5	0.993107682	93689.77685	1683806.504	17.97214767
2022	62	0.007722301	0.007692599	715.7504479	92686.16192	0.5	0.992307401	93044.03714	1590439.597	17.09340702
2022	63	0.008600801	0.008563972	790.696902	91932.93824	0.5	0.991436028	92328.28669	1497753.436	16.22204299
2022	64	0.009546751	0.009501397	869.7349696	9102.72231	0.5	0.990498603	91537.58979	1405820.497	15.35784917
2022	65	0.010551288	0.010495915	951.6421349	90192.03375	0.5	0.989504085	90667.85482	1314717.775	14.50037367
2022	66	0.011601808	0.011534895	1034.867071	9189.77915	0.5	0.988465105	89716.21269	1224525.741	13.64887911
2022	67	0.012682929	0.012603007	1117.65166	88122.51978	0.5	0.987396993	88681.34561	1135326.962	12.80231997
2022	68	0.013778345	0.013684074	1198.228026	86964.57994	0.5	0.986315926	87563.69395	1047204.442	11.95934519
2022	69	0.014873523	0.014763729	1275.076311	85727.92777	0.5	0.985236271	86365.46593	960239.8624	11.11833129
2022	70	0.015959042	0.015832704	1347.210965	84416.					

Table 21: Male Life Table in 2018

National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2018	Male	0	0.000692918	0.00069251	69.2509558	99940.99177	0.1479073	0.99930749	100000	7606231.514	76.06231514
2018	Male	1	0.000615938	0.000615748	61.5321898	99899.98295	0.5	0.999384252	99930.74904	7506290.522	75.11492302
2018	Male	2	0.000553216	0.000553063	55.23395549	99841.59988	0.5	0.99946937	99869.21685	7406390.539	74.16089534
2018	Male	3	0.000507455	0.000507327	50.63829344	99788.66375	0.5	0.999492673	99813.9829	7306548.939	73.20165699
2018	Male	4	0.000477524	0.00047741	47.62805067	99739.53058	0.5	0.99952259	99763.34461	7206760.275	72.2385592
2018	Male	5	0.000461019	0.000460912	45.96024063	99692.73645	0.5	0.999539088	99715.71655	7107020.745	71.27282429
2018	Male	6	0.00045313	0.00045209	45.37058862	99647.07106	0.5	0.999544791	99669.75635	7007328.008	70.3054594
2018	Male	7	0.000457856	0.000457751	45.60313854	99601.58419	0.5	0.999542249	99624.38576	6907680.937	69.33724996
2018	Male	8	0.000461168	0.000460659	46.40959735	99555.57782	0.5	0.999533941	99578.78262	6808079.353	68.36877469
2018	Male	9	0.00047778	0.00047766	47.54324171	99508.6014	0.5	0.999522334	99532.37303	6708523.775	67.4004203
2018	Male	10	0.000490222	0.000490102	48.7577413	99460.45091	0.5	0.999509898	99484.82978	6609015.174	66.43239163
2018	Male	11	0.000501103	0.000500978	49.81525981	99411.16441	0.5	0.999499022	99436.07204	6509554.723	65.46472109
2018	Male	12	0.000508279	0.00050815	50.50311637	99361.00522	0.5	0.99949185	99386.25678	6410143.559	64.49728329
2018	Male	13	0.000510064	0.000509934	50.654696495	99310.42632	0.5	0.999490066	99335.75367	6310782.553	63.52982003
2018	Male	14	0.000505422	0.000505295	50.16823169	99260.01485	0.5	0.999494705	99285.09897	6211472.127	62.56197749
2018	Male	15	0.000494074	0.000493952	49.01720724	99201.4221	0.5	0.999506048	99234.93074	6112212.112	61.59335293
2018	Male	16	0.000476483	0.00047637	47.24917092	99162.28888	0.5	0.99952363	99185.91347	6013001.69	60.62354502
2018	Male	17	0.000453728	0.000453625	44.97177501	99116.17841	0.5	0.999546375	99138.6643	5913839.401	59.6521997
2018	Male	18	0.000427282	0.000427191	43.33192899	99072.52656	0.5	0.999572809	99093.69252	5814723.223	58.6790448
2018	Male	19	0.000398776	0.000398696	39.4913932	99031.6149	0.5	0.999601304	99051.36059	5715650.696	57.70390898
2018	Male	20	0.000369776	0.000369708	36.60543646	98993.56648	0.5	0.999630299	99011.8692	5616619.081	56.72672505
2018	Male	21	0.000341635	0.000341576	33.8076118	98958.35996	0.5	0.999658424	98975.26376	5517625.515	55.74752019
2018	Male	22	0.000315407	0.000315357	31.20187558	98925.85521	0.5	0.999684643	98941.45615	5418667.155	54.76639788
2018	Male	23	0.000291853	0.000291792	28.8612552	98895.82365	0.5	0.999708208	98910.25428	5319741.3	53.78351657
2018	Male	24	0.000271384	0.000271347	26.83118872	98867.97743	0.5	0.999728653	98881.39302	5220845.476	52.79906883
2018	Male	25	0.000254299	0.000254267	25.13542788	98841.99412	0.5	0.999745733	98854.56183	5121977.499	51.81326389
2018	Male	26	0.000240673	0.000240644	23.78274493	98817.53503	0.5	0.999759356	98829.4264	5023135.504	50.82631446
2018	Male	27	0.000230512	0.000230486	22.7732712	98794.25702	0.5	0.999769514	98805.64366	4924317.969	49.83842812
2018	Male	28	0.000223787	0.000223762	20.1086945	98771.81845	0.5	0.999776238	98782.87039	4825523.712	48.84980254
2018	Male	29	0.000220408	0.000220456	21.7727348	98749.88033	0.5	0.99979544	98760.76652	4726751.894	47.86062381
2018	Male	30	0.000220614	0.00022059	21.78078957	98728.10375	0.5	0.999779491	98738.99415	4628002.014	46.87106704
2018	Male	31	0.000224279	0.000224253	22.13767237	98706.14452	0.5	0.999775747	98717.21336	4529273.91	45.88129826
2018	Male	32	0.000231648	0.000231622	22.85990964	98683.64573	0.5	0.999768378	98695.07568	4430567.765	44.89147746
2018	Male	33	0.000242997	0.000242967	23.97411824	98660.22871	0.5	0.999757033	98672.21577	43.31884.12	43.90176187
2018	Male	34	0.000258708	0.000258675	25.51779808	98635.48276	0.5	0.999741325	98648.24166	4233223.891	42.91230964
2018	Male	35	0.000279288	0.000279249	25.4033236	98608.95369	0.5	0.999720751	98622.72386	4134588.408	41.92328346
2018	Male	36	0.000305375	0.000305328	30.10387053	98580.13159	0.5	0.9996946472	98595.18532	4035979.454	40.93485412
2018	Male	37	0.000337743	0.000337686	33.2840189	98548.43761	0.5	0.999662314	98565.07965	3937399.323	39.94720378
2018	Male	38	0.000377318	0.000377247	37.17082703	98513.21015	0.5	0.999622753	98531.79556	3838850.885	38.96052907
2018	Male	39	0.000425175	0.000425084	41.861851354	98473.69048	0.5	0.999574916	98494.62474	3740337.675	37.97504366
2018	Male	40	0.000482546	0.000482429	47.49648357	98429.00798	0.5	0.999517571	98452.75622	3641863.985	36.99090849
2018	Male	41	0.000550825	0.000550673	54.18912372	98378.16518	0.5	0.999449327	98405.25974	3543434.977	36.0085933
2018	Male	42	0.00063157	0.000631371	62.0960605	98320.02261	0.5	0.999368629	98351.07061	3445056.811	35.0281577
2018	Male	43	0.000726512	0.000726248	71.38215807	98253.28353	0.5	0.999273752	98288.97461	3346736.789	34.04997155
2018	Male	44	0.00083756	0.000837209	82.22868362	98176.47811	0.5	0.999162791	98217.59245	3248483.505	33.07435485
2018	Male	45	0.000966826	0.000966359	43.84300164	98087.94767	0.5	0.999033641	98135.36377	3150307.027	32.10164926
2018	Male	46	0.01116651	0.01116027	109.4159226	97985.82118	0.5	0.998883973	98040.52976	3052219.08	31.13221734
2018	Male	47	0.001289642	0.001288811	126.2147328	97868.00648	0.5	0.998711189	97931.11384	2954233.259	30.16644193
2018	Male	48	0.01488735	0.01488735	145.4973021	97732.15046	0.5	0.998512372	97804.89911	2856365.252	29.20472572
2018	Male	49	0.001717253	0.00171758	167.5620277	97575.62079	0.5	0.998284222	97659.40181	2758633.102	28.24749129
2018	Male	50	0.001978985	0.001977029	192.7441626	97395.4677	0.5	0.998022971	97491.83978	2661057.481	27.2951817
2018	Male	51	0.002272864	0.002275671	221.4207695	97188.38523	0.5	0.997724329	97299.09562	2563662.013	26.34826148
2018	Male	52	0.002620036	0.002616608	254.0142039	96950.66775	0.5	0.997383392	97077.67485	2466473.628	25.4072178
2018	Male	53	0.003009911	0.003005388	299.9926794	96678.1643	0.5	0.996994612	96823.66064	2369522.96	24.4725612
2018	Male	54	0.003454178	0.003448223	332.8661271	96366.2349	0.5	0.996551777	96532.66796	2272844.796	23.54482523
2018	Male	55	0.003959758	0.003951934	380.1752739	96009.7142	0.5	0.996048066	96199.80184	2176478.561	22.62456387
2018	Male	56	0.004534086	0.00452383	433.471703	95602.89071	0.5	0.99547617	95819.62656	2080468.847	21.7123456
2018	Male	57	0.005184878	0.005174171	493.2867649	95139.51148	0.5	0.994828529	95386.15486	1984865.956	20.80874273
2018	Male	58	0.005919787	0.005902316	560.0877408	94612.82422	0.5	0.994097684	94892.86809	1889726.445	19.91431477
2018	Male	59	0.006745906	0.006723229	634.2208716	94015.66992	0.5	0.993276771	94332.78035	1795113.62	19.02958456
2018	Male	60	0.007669145	0.00763985	715.8429332	93340.63802	0.5	0.99236015	93698.55948	1701097.95	18.15500644
2018	Male	61	0.008693492	0.008655867	804.8460728	92580.29351	0.5	0.991344133	92982.71655	1607757.312	17.29092644
2018	Male	62	0.009820224	0.009772241	900.7844099	91727.47827	0.5	0.99027759	92177.87048	1515177.019	16.4375351
2018	Male	63	0.011047176	0.010984911	1002.814854	90775.67864	0.5	0.989013509	91277.08607	1423449.541	15.59481796
2018	Male	64	0.012368195	0.012291797	1109.667537	98719.43744	0.5	0.987707821	90274.27121	1332673.862	14.76249926
2018	Male	65	0.013772963	0.013678765	1219.661645	88554.77285	0.5	0.986321235	89164.60368	1242954.425	13.93999831
2018	Male	66	0.015247313	0.01513952	1330.778674	87279.55269	0.5	0.984868048	87944.94203	1154399.652	13.1263905
2018	Male	67	0.016774166	0.01663465	1440.796252	85893.76523	0.5	0.983365353	86614.16336	10	

Table 22: Male Life Table in 2019

National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2019	Male	0	0.000803777	0.000803227	80.32271554	99931.53983	0.1476861	0.999196773	100000	7531438.821	75.31438821
2019	Male	1	0.000714481	0.000714226	71.36520963	99883.99468	0.5	0.999285774	99919.67728	7431507.282	74.37481269
2019	Male	2	0.000641724	0.000641518	64.05405826	99816.28482	0.5	0.999358482	99848.31207	7331623.287	73.42761369
2019	Male	3	0.000588642	0.000588469	58.71996219	99754.89759	0.5	0.999411531	99784.25757	7231807.002	72.47442812
2019	Male	4	0.000553923	0.000553769	55.22494517	99697.92513	0.5	0.999446231	99725.5376	7132052.105	71.51680779
2019	Male	5	0.000534776	0.000534633	53.28706911	99643.66912	0.5	0.999465367	99670.31266	7032354.179	70.55615651
2019	Male	6	0.000528158	0.000528018	52.59960215	99590.72579	0.5	0.999471982	99617.02559	6932710.51	69.5936309
2019	Male	7	0.000531107	0.000530966	52.865343	99537.99332	0.5	0.999469034	99564.42599	6833119.784	68.63013287
2019	Male	8	0.000540749	0.000540603	53.79625212	99484.66252	0.5	0.999459397	99511.56064	6733581.791	67.66632688
2019	Male	9	0.00055422	0.000554066	55.10616862	99430.21131	0.5	0.999445934	99457.76439	6634097.129	66.70265684
2019	Male	10	0.000568652	0.000568491	56.50948844	99374.40348	0.5	0.999431509	99402.65822	6534666.917	65.73935782
2019	Male	11	0.000581274	0.000581105	57.73055827	99317.28346	0.5	0.999418895	99346.14874	6435292.514	64.77646689
2019	Male	12	0.000589598	0.000589424	58.52298458	99259.15669	0.5	0.999410576	99288.41818	6335975.23	63.81383999
2019	Male	13	0.000591669	0.000591494	58.69385428	99200.54827	0.5	0.999408506	99229.89519	6236716.074	62.8511807
2019	Male	14	0.000586284	0.000586112	58.12546318	99142.13861	0.5	0.999413888	99171.20134	6137515.525	61.88808286
2019	Male	15	0.00057312	0.000572956	58.78740603	99084.68217	0.5	0.999427044	99113.07588	6038373.387	60.92408427
2019	Male	16	0.000552715	0.000552652	54.7347808	99028.92108	0.5	0.99947438	99056.28847	5939288.705	59.95872444
2019	Male	17	0.000526319	0.000526181	52.09270425	98975.50734	0.5	0.999473819	99001.55369	5840259.784	58.99159726
2019	Male	18	0.000495642	0.00049552	49.03140354	98924.94528	0.5	0.99950448	98949.46098	5741284.276	58.02239061
2019	Male	19	0.000462575	0.000462468	45.7380059	98877.56043	0.5	0.999537532	98900.42958	5642359.331	57.05090822
2019	Male	20	0.000428936	0.000428844	42.3932504	98833.49467	0.5	0.999571156	98854.69128	5534381.771	56.07707332
2019	Male	21	0.000396292	0.000396214	39.15080032	98792.72265	0.5	0.999603786	98812.29805	5444648.276	55.10091743
2019	Male	22	0.000365868	0.000365801	36.13133643	98755.08159	0.5	0.999634199	98773.14723	5345855.553	54.12255964
2019	Male	23	0.000338525	0.000338468	33.41930727	98720.30626	0.5	0.999661532	98737.01592	5247100.472	53.14218202
2019	Male	24	0.000314802	0.000314753	31.06723304	98688.06299	0.5	0.999685247	98703.59661	5148380.165	52.16000574
2019	Male	25	0.000294984	0.000294941	29.10252657	98657.97812	0.5	0.999705059	98672.52938	5049692.102	51.17627099
2019	Male	26	0.000279178	0.000279193	27.53525993	98629.65922	0.5	0.999720861	98643.42685	4951034.124	50.19122188
2019	Male	27	0.000267391	0.000267356	26.36551452	98602.70884	0.5	0.999732644	98615.89159	4852404.465	49.20509653
2019	Male	28	0.000259591	0.000259557	25.58959171	98576.73128	0.5	0.999740443	98589.52608	4753801.756	48.21812159
2019	Male	29	0.000255754	0.000255722	25.20492393	98551.33402	0.5	0.999744278	98563.93649	4655225.025	47.23051038
2019	Male	30	0.000255951	0.000255877	25.1377719	98526.12467	0.5	0.999744123	98538.73156	4556673.691	46.24246343
2019	Male	31	0.000260161	0.000260127	25.62599819	98500.70479	0.5	0.999739873	98513.51778	4458147.566	45.25417086
2019	Male	32	0.000268709	0.000268673	26.4167032	98474.66125	0.5	0.999731327	98487.89179	4359646.861	44.26581563
2019	Male	33	0.000281873	0.000281834	27.74797547	98447.55583	0.5	0.999718166	98461.43071	4261172.2	43.27757752
2019	Male	34	0.000300098	0.000300053	29.53536032	98418.91328	0.5	0.999699947	98433.68096	4162724.644	42.28963708
2019	Male	35	0.000323971	0.000323919	31.87495378	98388.20812	0.5	0.999676081	98404.1456	4064305.731	41.30217997
2019	Male	36	0.000354231	0.000354168	34.84034225	98354.85047	0.5	0.999645832	98372.27064	3965917.523	40.31540085
2019	Male	37	0.000391779	0.000391702	38.51895045	98318.17082	0.5	0.999608298	98337.4303	3867562.672	39.32950719
2019	Male	38	0.000347685	0.000347589	43.0145234	98277.40409	0.5	0.999562411	98289.91135	3769244.502	38.34472274
2019	Male	39	0.000493198	0.000493076	48.44763204	98231.67301	0.5	0.999506924	98255.89683	3670967.098	37.36129043
2019	Male	40	0.000559747	0.000559591	54.95597737	98179.9712	0.5	0.999440409	98207.44919	3572735.425	36.37947481
2019	Male	41	0.000638959	0.000638746	62.69453817	98121.14595	0.5	0.999361254	98152.49322	3474555.453	35.39956388
2019	Male	42	0.000732614	0.000732346	71.83567458	98053.88084	0.5	0.999267654	98089.79868	3376434.307	34.42187009
2019	Male	43	0.000842745	0.000842399	82.56937521	97976.67832	0.5	0.999157161	98017.963	3278380.427	33.44673085
2019	Male	44	0.00097156	0.000971088	95.10390032	97887.84168	0.5	0.999028912	97935.39363	3180403.748	32.47450825
2019	Male	45	0.001121507	0.001120879	109.6671063	97785.45617	0.5	0.998879121	97840.28973	3082515.907	31.5055885
2019	Male	46	0.001295302	0.001294463	126.5087192	97667.36826	0.5	0.998705537	97730.62262	2984730.45	30.540381
2019	Male	47	0.00149597	0.001494852	145.9037301	97531.16204	0.5	0.998505148	97604.1139	2887063.082	29.57931758
2019	Male	48	0.001726916	0.001725426	168.1569229	97374.13171	0.5	0.998274574	97458.21017	2789531.92	28.62285194
2019	Male	49	0.001991994	0.001990902	193.6083442	97193.24907	0.5	0.998009988	97290.05324	2692157.788	27.67145971
2019	Male	50	0.0022956	0.002292968	222.6390316	96985.12538	0.5	0.997707032	97096.4449	2594964.539	26.72563905
2019	Male	51	0.00264276	0.002639275	25.56763445	96745.96769	0.5	0.997360728	96873.80587	2497979.414	25.7859118
2019	Male	52	0.003039211	0.003030436	293.1973588	96471.53084	0.5	0.9969654	96618.12952	2401233.446	24.85282481
2019	Male	53	0.003491462	0.003485378	335.7287747	96157.06778	0.5	0.996514622	96324.93216	2304761.915	23.92695083
2019	Male	54	0.004006807	0.003998796	383.8412005	95979.28279	0.5	0.996001204	95989.20339	2208604.848	23.00888818
2019	Male	55	0.004593274	0.004582749	438.1354104	95386.29448	0.5	0.995417251	95605.36219	2112807.565	22.099258
2019	Male	56	0.00529487	0.005246593	499.2180091	94917.61777	0.5	0.994754307	95167.22678	2017421.27	21.19869769
2019	Male	57	0.006014399	0.00596367	567.6640931	94384.17672	0.5	0.994003633	94668.00877	1922503.653	20.30784927
2019	Male	58	0.006686885	0.006843883	643.9651868	93778.36208	0.5	0.993156612	94100.34468	1828119.476	19.42734091
2019	Male	59	0.007825173	0.007794676	728.4622054	93092.14839	0.5	0.992205324	93456.37949	1734341.114	18.55776056
2019	Male	60	0.008896121	0.008856725	821.2656981	92317.28443	0.5	0.991143275	92727.91728	1641248.965	17.69962071
2019	Male	61	0.010084351	0.010033795	922.1692131	91445.56698	0.5	0.989966241	91906.65158	1548931.681	16.85331425
2019	Male	62	0.011391347	0.011326833	1030.56607	90469.19934	0.5	0.988673167	90984.48237	1457486.114	16.01906255
2019	Male	63	0.012814597	0.012733012	1145.384333	89381.22414	0.5	0.987266988	89953.9163	1367016.915	15.19685825
2019	Male	64	0.014346965	0.01424478	1265.05799	88176.00297	0.5	0.98575522	88808.53197	1277635.691	14.38640705
2019	Male	65	0.015976479	0.015849867	1387.55329	86849.69778	0.5	0.984150133	87543.47398	118945.688	13.58707432
2019	Male	66	0.017686708	0.017531669	1510.457124	85400.69302	0.5	0.982468331	86155.92159	1102609.99	12.79784337
2019	Male	67	0.019457839	0.01927036	1631.148544	83829.89019	0.5	0.98072964	84645.		

Table 23: Male Life Table in 2020

National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2020	Male	0	0.000932373	0.000931632	93.16320054	99920.5718	0.1474295	0.999068368	100000	7448257.766	74.48257766
2020	Male	1	0.00082879	0.00082846	82.76745585	99865.45307	0.5	0.999171554	99906.8368	7348337.195	73.55189525
2020	Male	2	0.000744392	0.000744116	74.28064113	99786.92902	0.5	0.999255884	99824.06934	7248471.742	72.612465
2020	Male	3	0.000682818	0.000682585	68.08774701	99715.74483	0.5	0.999317415	99749.7887	7148684.813	71.66616497
2020	Male	4	0.000642544	0.000642338	64.02930609	99649.6863	0.5	0.999357662	99681.70096	7048969.068	70.71477513
2020	Male	5	0.000620334	0.000620142	61.7709935	99586.7831	0.5	0.999379858	99617.67165	6949319.381	69.75990571
2020	Male	6	0.000612657	0.000612469	60.97491599	99525.40709	0.5	0.999387531	99555.89455	6849732.598	68.80288334
2020	Male	7	0.000616078	0.000615889	61.27777756	99464.28075	0.5	0.999384111	99494.91963	6750207.191	67.84472439
2020	Male	8	0.000627263	0.000627066	62.3514754	99402.46612	0.5	0.999372934	99433.64186	6650742.911	66.8862448
2020	Male	9	0.000642888	0.000642682	63.86411391	99339.35832	0.5	0.999357318	99371.29038	6551340.444	65.92789949
2020	Male	10	0.000659633	0.000659413	65.4845791	99274.68398	0.5	0.999340587	99307.42627	6452001.086	64.96997585
2020	Male	11	0.000674271	0.000674044	66.89343112	99208.49497	0.5	0.999325956	99241.94169	6352726.402	64.01251622
2020	Male	12	0.000683927	0.000683693	67.80527886	99141.14562	0.5	0.999316307	99175.04826	6253517.907	63.05535532
2020	Male	13	0.000686329	0.000686093	67.99682417	99073.24457	0.5	0.999313907	99107.24298	6154376.761	62.09815324
2020	Male	14	0.000680083	0.000679852	67.33199816	99005.58015	0.5	0.999320148	99039.24615	6055303.517	61.14044434
2020	Male	15	0.000664813	0.000664592	65.77594044	98939.0262	0.5	0.999335408	98971.91416	5956297.937	60.18169889
2020	Male	16	0.000641143	0.000640938	63.39267338	98874.41491	0.5	0.999359062	98906.13825	5857358.911	59.22138923
2020	Male	17	0.000610524	0.000610338	60.32746825	98812.58184	0.5	0.999389662	98842.74558	5758484.469	58.25905012
2020	Male	18	0.000574794	0.000574774	56.77759821	98754.02931	0.5	0.999425226	98782.41811	5659671.887	57.29432418
2020	Male	19	0.000536582	0.000536438	52.96017678	98699.16042	0.5	0.999463092	98725.64051	5560917.857	56.32698688
2020	Male	20	0.000497561	0.000497437	49.08342793	98648.13862	0.5	0.999502563	98672.68033	5462218.697	55.35695066
2020	Male	21	0.000459695	0.000459589	45.32631407	98600.93375	0.5	0.999540411	98623.59691	5363570.558	54.38425211
2020	Male	22	0.000424403	0.000424313	41.82801993	98557.35658	0.5	0.999575687	98578.27059	5264696.625	53.40902811
2020	Male	23	0.000392685	0.000392608	38.686216	98517.09946	0.5	0.999607392	98536.44257	5166412.268	52.43148761
2020	Male	24	0.000365167	0.0003651	35.96157354	98479.77557	0.5	0.9996349	98497.75636	5067895.169	51.45188435
2020	Male	25	0.000342178	0.000342123	31.6857024	98444.95193	0.5	0.999657588	98461.79478	4969415.393	50.4704937
2020	Male	26	0.000323844	0.000323791	31.87015384	98412.174	0.5	0.999676209	98428.10908	4870970.441	49.48759543
2020	Male	27	0.000310171	0.000310123	30.51492042	98380.98147	0.5	0.999689877	98396.23893	4772558.267	48.50346232
2020	Male	28	0.000301122	0.000301077	46.1563436	98350.91619	0.5	0.999698923	98365.72401	4674177.286	47.51835391
2020	Male	29	0.000296672	0.000296628	29.16924379	98321.52375	0.5	0.999703372	98336.10837	4575826.369	46.5325143
2020	Male	30	0.000296852	0.000296808	29.17829523	98292.34998	0.5	0.999701932	98306.93913	4477504.846	45.54617289
2020	Male	31	0.000301783	0.000301738	29.65410806	98262.93378	0.5	0.999698262	98277.76083	4379212.496	44.55954693
2020	Male	32	0.0003117	0.000311651	30.1915539	98232.79715	0.5	0.999688349	98248.10673	4280949.562	43.57284537
2020	Male	33	0.00032697	0.000326917	32.10892185	98201.43311	0.5	0.999670383	98217.48757	4182716.765	42.58627326
2020	Male	34	0.000348111	0.00034805	34.17343453	98168.29193	0.5	0.99965195	98185.37865	4084515.332	41.60003646
2020	Male	35	0.000375803	0.000375732	36.87858409	98132.76592	0.5	0.999624268	98151.20521	3986347.04	40.61434632
2020	Male	36	0.000410904	0.00041082	40.30728317	98094.17299	0.5	0.99958918	98114.32663	3888214.274	39.62942424
2020	Male	37	0.000454459	0.000454355	44.56045762	98051.73912	0.5	0.999545645	98074.01935	3790120.101	38.64550598
2020	Male	38	0.000507709	0.000507598	49.75783742	98044.57997	0.5	0.99949242	98029.45889	3692068.362	37.66284547
2020	Male	39	0.000572104	0.00057194	56.03851234	97951.68179	0.5	0.99942806	97979.70105	3594063.782	36.68171818
2020	Male	40	0.0006493	0.00064909	63.5612456	97891.88192	0.5	0.99935091	97923.66254	3496112.1	35.7024238
2020	Male	41	0.000741175	0.000740749	52.50459462	97823.849	0.5	0.9992591	97860.10129	3398220.218	34.72528817
2020	Male	42	0.000849824	0.000849463	83.06696601	97746.06322	0.5	0.999150537	97787.5967	3300396.369	33.75066451
2020	Male	43	0.000977575	0.000977097	95.46681767	97656.79632	0.5	0.999022903	97704.52973	3202650.306	32.77893374
2020	Male	44	0.001126998	0.001126364	109.9432951	97554.09127	0.5	0.998873636	97609.06291	3104993.51	31.81050424
2020	Male	45	0.001300936	0.00130009	126.7576259	97435.74081	0.5	0.99869991	97499.11962	3007439.418	30.84581102
2020	Male	46	0.001502535	0.001501407	146.195571	97299.26421	0.5	0.998498593	97372.36199	2910003.677	29.88531466
2020	Male	47	0.001735308	0.001733804	168.5711271	97141.88086	0.5	0.998266196	97226.16642	2812704.413	28.92950033
2020	Male	48	0.002003203	0.002001198	194.2314747	96960.47956	0.5	0.997998802	97057.5953	2715562.532	27.97887712
2020	Male	49	0.002310690	0.002308023	223.5628992	96751.58237	0.5	0.997691977	96863.36382	2618602.053	27.03397807
2020	Male	50	0.002662869	0.002659329	256.9969891	96511.30242	0.5	0.997340671	96639.80092	2521850.47	26.09536078
2020	Male	51	0.003065571	0.003060879	295.0161203	96235.29587	0.5	0.996939121	96382.80393	2425339.168	25.16360875
2020	Male	52	0.00352545	0.003519247	338.1566223	95918.7095	0.5	0.996480753	96087.78781	2329103.872	24.23933286
2020	Male	53	0.004050056	0.004041871	387.0076775	95556.12735	0.5	0.995598129	95749.63119	2233185.163	23.32317248
2020	Male	54	0.00464785	0.004637074	442.2035021	95141.52176	0.5	0.995362926	95362.62351	2137629.035	22.41579517
2020	Male	55	0.005328145	0.005313988	504.4060191	94668.217	0.5	0.994686012	94920.42001	2042487.514	21.51789376
2020	Male	56	0.006109045	0.006082391	574.2750854	94128.87645	0.5	0.993917609	94146.01399	1947819.297	20.63017929
2020	Male	57	0.006976634	0.006952382	652.4235735	93515.52712	0.5	0.993047618	93841.7389	1853690.442	19.75336819
2020	Male	58	0.007965507	0.007933908	739.3554848	92819.63759	0.5	0.992066092	93189.31333	1760174.893	18.88816209
2020	Male	59	0.009077111	0.0090361	835.387118	92032.26628	0.5	0.9909639	92449.95984	1667355.255	18.03521882
2020	Male	60	0.010319398	0.010266426	940.5542324	91144.29561	0.5	0.989733574	91614.57272	1575322.989	17.19511364
2020	Male	61	0.011697731	0.011629711	104.5126161	91046.76218	0.5	0.988370289	90674.01849	1484178.694	16.3682907
2020	Male	62	0.013213832	0.013127102	117.644422	90813.28366	0.5	0.986872898	90819.50587	1394031.931	15.55500577
2020	Male	63	0.014864785	0.014755119	1304.987893	87790.56751	0.5	0.985244881	88443.06145	1305000.648	14.75526317
2020	Male	64	0.016642314	0.016504974	1438.211596	86418.96776	0.5	0.983495026	87183.07356	1217210.08	13.96875132
2020	Male	65	0.018532532	0.018362382	1573.653567	84913.03518	0.5	0.981637618	85699.86196	1130791.112	13.19478336
2020	Male	66	0.020516375	0.020308054	1708.439599	83271.9886	0.5	0.979691946	84126.2084	1045878.077	12.43225027
2020	Male	67	0.02257087	0.022318991	1839.481407	81498.02809	0.5	0.977681009	82417.7688	962606	

Table 24: Male Life Table in 2021

National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2021	Male	0	0.001081541	0.001080545	108.054476	99907.84377	0.1471318	0.998919455	100000	7356276.977	73.56276977
2021	Male	1	0.000961386	0.000960925	95.98862589	99843.95121	0.5	0.999039075	99891.94552	7256369.134	72.64218447
2021	Male	2	0.000863487	0.000863114	86.13529707	99752.88925	0.5	0.999136886	99795.9569	7156525.182	71.71157434
2021	Male	3	0.000792062	0.000791748	78.94504774	99670.34908	0.5	0.999208252	99709.8216	7056772.293	70.77309115
2021	Male	4	0.000745344	0.000745066	74.2315754	99593.76077	0.5	0.999254934	99630.87655	6957101.944	69.82877382
2021	Male	5	0.000719581	0.000719322	71.61327264	99520.83834	0.5	0.999280678	99556.64498	6857508.183	68.88046684
2021	Male	6	0.000710675	0.000710422	70.676394	99449.69351	0.5	0.999289578	99485.03171	6757987.345	67.92968981
2021	Male	7	0.000714644	0.000714388	71.02046161	99378.84508	0.5	0.999285612	99414.35531	6658537.651	66.97762743
2021	Male	8	0.000727618	0.000727353	72.25768189	99307.20601	0.5	0.999272647	99343.33485	6559158.806	66.02515223
2021	Male	9	0.000745473	0.000745465	74.00312426	99234.07561	0.5	0.999254535	99271.07717	6459851.6	65.07284684
2021	Male	10	0.000765163	0.000764871	75.87294722	99159.13757	0.5	0.999235129	99197.07404	6360617.525	64.12101956
2021	Male	11	0.000782147	0.000781841	77.4970276	99082.45258	0.5	0.999218159	99121.2011	6261458.387	63.16971867
2021	Male	12	0.000793347	0.000793038	78.5448251	99040.43163	0.5	0.999206967	99043.70407	6162375.935	62.21875477
2021	Male	13	0.000796134	0.000795817	78.75813312	98925.78012	0.5	0.999204183	98965.15919	6063371.503	61.26773859
2021	Male	14	0.000788888	0.000788577	77.9795664	98847.41127	0.5	0.999211423	98886.40105	5964445.723	60.3161371
2021	Male	15	0.000771175	0.000770878	76.16920414	98770.33688	0.5	0.999229122	98808.42149	5865598.312	59.36334397
2021	Male	16	0.000743719	0.000743442	73.4017283	98695.55142	0.5	0.999256558	98732.25228	5766827.975	58.40875541
2021	Male	17	0.000708201	0.00070795	69.8455648	98623.92777	0.5	0.99929205	98658.85055	5668132.423	57.45183926
2021	Male	18	0.000666923	0.000666701	65.72938456	98556.1403	0.5	0.999333299	98589.00449	5569508.495	56.49218689
2021	Male	19	0.000622429	0.000622235	61.3046171	98492.62328	0.5	0.999377765	98523.2756	5470952.355	55.52954184
2021	Male	20	0.000577165	0.000576998	56.81236783	98433.56478	0.5	0.999423002	98461.97096	5372459.732	54.56380447
2021	Male	21	0.00053324	0.000533098	52.45962134	98378.92878	0.5	0.999466902	98405.1586	5274026.167	53.5950172
2021	Male	22	0.000492302	0.000492181	48.4073541	98328.4953	0.5	0.999507819	98352.69897	5175647.238	52.62333716
2021	Male	23	0.0004551	0.000455407	44.76843349	98281.9074	0.5	0.999544593	98304.29162	5077318.743	51.64900392
2021	Male	24	0.00042359	0.0004235	41.61290196	98238.71674	0.5	0.9995765	98259.52319	4979036.836	50.67230813
2021	Male	25	0.000396923	0.000396844	38.97717419	98198.4217	0.5	0.999603156	98217.91029	4880798.119	49.6935651
2021	Male	26	0.000375655	0.000375584	36.87446804	98160.49588	0.5	0.999624416	98178.93311	4782599.697	48.71309502
2021	Male	27	0.000359795	0.00035973	35.30464259	98124.40632	0.5	0.99964027	98142.05864	4684439.201	47.7312099
2021	Male	28	0.000349298	0.000349237	34.26252614	98089.62274	0.5	0.999650763	98106.754	4586314.795	46.7482065
2021	Male	29	0.000341436	0.000344077	33.74448019	98055.61923	0.5	0.999655923	98072.49147	4488225.172	45.76436373
2021	Male	30	0.000344345	0.000344286	33.75334876	98021.87032	0.5	0.999655714	98038.74699	4390169.553	44.77994352
2021	Male	31	0.000350065	0.000350004	34.30212469	97987.84258	0.5	0.999649996	98004.99365	4292147.683	43.79519372
2021	Male	32	0.000361568	0.000361503	35.41669661	97952.98317	0.5	0.999638497	97970.69152	4194159.84	42.81035251
2021	Male	33	0.000379281	0.000379291	37.13798853	97916.70583	0.5	0.99962079	97935.27482	4096206.857	41.82565336
2021	Male	34	0.000403804	0.000403723	39.52372153	97878.37497	0.5	0.999596277	97898.13684	3998290.151	40.84133039
2021	Male	35	0.000435927	0.000435823	42.6499621	97837.28815	0.5	0.999564168	97858.61311	3900411.776	39.85762369
2021	Male	36	0.000476644	0.00047653	46.16226948	97792.65705	0.5	0.99952347	97815.96319	3802574.488	38.87478448
2021	Male	37	0.000527167	0.000527028	51.5271713	97743.58733	0.5	0.999472972	97769.35092	3704781.831	37.89307995
2021	Male	38	0.000588937	0.000588764	57.53269661	97698.054	0.5	0.999411236	97717.82375	3607038.244	36.91279754
2021	Male	39	0.000663634	0.000663413	64.78915541	97627.89647	0.5	0.999336587	97660.29105	3509349.186	35.93424869
2021	Male	40	0.000753181	0.000752898	73.47941487	97558.76219	0.5	0.999247102	97595.50189	3411721.29	34.95777186
2021	Male	41	0.000859755	0.000859385	83.80897215	97480.11799	0.5	0.999140615	97522.02248	3314162.528	33.98373458
2021	Male	42	0.000985786	0.000985301	96.00593116	97390.21054	0.5	0.999014699	97438.21351	3216682.41	33.01253475
2021	Male	43	0.001133975	0.001133333	110.3211246	97287.04701	0.5	0.998866667	97342.20758	3119292.199	32.04460097
2021	Male	44	0.001307305	0.001306451	127.0287061	97168.3721	0.5	0.9986933549	97231.88645	3022005.152	31.08039206
2021	Male	45	0.00150907	0.001507933	146.4275786	97031.64396	0.5	0.998492067	97104.85775	2924836.78	30.12039611
2021	Male	46	0.001742924	0.001741406	168.8439932	96874.00817	0.5	0.998258594	96958.43017	2827805.136	29.16512913
2021	Male	47	0.002012938	0.002010914	194.635528	96692.26841	0.5	0.997989086	96789.58617	2730931.128	28.21513384
2021	Male	48	0.002323692	0.002320995	224.1964226	96482.85243	0.5	0.997790075	96594.95065	2634238.859	27.27097888
2021	Male	49	0.002680374	0.002676786	257.963912	96241.72277	0.5	0.997323214	96370.54222	2537756.007	26.33325875
2021	Male	50	0.003088898	0.003084135	296.4247774	95964.57792	0.5	0.996915865	96112.79031	2441514.235	25.40259446
2021	Male	51	0.003556027	0.003549716	340.1208418	95646.30511	0.5	0.996450284	95816.36553	2345549.657	24.47963501
2021	Male	52	0.004089482	0.004081137	389.651607	95281.41889	0.5	0.995918863	95476.24469	2249903.352	23.56505913
2021	Male	53	0.004698019	0.004687009	445.6716902	94863.75724	0.5	0.995312991	95086.59308	2154621.933	22.65957653
2021	Male	54	0.005391452	0.005376958	508.8802153	94386.48129	0.5	0.994623042	94640.92139	2059758.175	21.76392775
2021	Male	55	0.006180587	0.006161549	579.9989363	93842.04171	0.5	0.993838454	94132.04118	1965371.694	20.87888109
2021	Male	56	0.007070206	0.007052027	659.7357445	93222.17437	0.5	0.992947928	93552.04224	1871529.652	20.00522498
2021	Male	57	0.008092815	0.0080602	748.7305868	92517.94121	0.5	0.9919398	92892.3065	1778307.478	19.14375415
2021	Male	58	0.009239897	0.009197405	847.4818066	91719.85053	0.5	0.990802595	92143.57593	1685789.537	18.29524761
2021	Male	59	0.010529345	0.010474201	956.2536825	90817.96728	0.5	0.989525799	91296.09412	1594069.702	17.46043702
2021	Male	60	0.011970383	0.011899164	1074.96857	89802.35616	0.5	0.988100836	90339.84044	1503251.735	16.63996446
2021	Male	61	0.013569234	0.013477792	1203.093143	88663.32516	0.5	0.986522208	89264.87187	1413449.378	15.83432933
2021	Male	62	0.015237893	0.015211314	1339.535406	87392.01075	0.5	0.984788686	88061.77846	1324786.053	15.04382578
2021	Male	63	0.01724298	0.01709559	1482.567917	85980.95909	0.5	0.98290441	86722.24305	1237394.042	14.26847368
2021	Male	64	0.019304893	0.019120335	1629.811139	84424.76956	0.5	0.980879665	85239.67513	1151413.083	13.50794781
2021	Male	65	0.021497524	0.02126891	1778.290672	82720.71866	0.5	0.97873109	83609.864	1066988.314	12.76151237
2021	Male	66	0.023798763	0.023518902	1924.588781	80869.27893	0.5	0.976481098	81831.57332	984267.5952	12.02796861
2021	Male	67	0.02618195	0.025843632	2065.086669	78874.44121	0.5	0.974156368	79906.98454	90339	

Table 25: Male Life Table in 2022

National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2022	Male	0	0.001254576	0.001253234	125.3234184	99893.07238	0.1467866	0.998746766	100000	7255206.252	72.55206252
2022	Male	1	0.001115197	0.001114576	111.3178969	99819.01763	0.5	0.998885424	99874.67658	7155313.18	71.64291715
2022	Male	2	0.001001635	0.001001133	99.87642131	99713.42047	0.5	0.998989867	99763.35868	7055494.162	70.7222998
2022	Male	3	0.000918782	0.00091836	91.52699233	99617.71877	0.5	0.99908164	99663.48226	6955780.742	69.79267214
2022	Male	4	0.00086459	0.000864216	86.05172174	99528.92941	0.5	0.999135784	99571.95527	6856163.023	68.85636628
2022	Male	5	0.000834705	0.000834357	83.00676982	99444.40016	0.5	0.999165643	99485.90355	6756634.094	67.91549207
2022	Male	6	0.000824375	0.000824035	81.91146381	99361.94105	0.5	0.999175965	99402.89678	6657189.693	66.97178763
2022	Male	7	0.000828978	0.000828635	82.30084189	99279.83489	0.5	0.999171365	99320.98532	6557827.752	66.02660788
2022	Male	8	0.000844028	0.000843672	83.7249133	99196.82202	0.5	0.999156328	99238.68447	6458547.917	65.08095055
2022	Male	9	0.000865053	0.000864679	85.73725033	99112.09094	0.5	0.999135155	99154.95956	6359351.095	64.13548171
2022	Male	10	0.000887581	0.000887187	87.89293363	99025.27584	0.5	0.999112813	99069.22231	6260239.004	63.19055362
2022	Male	11	0.000907281	0.00090687	89.76319387	98936.44778	0.5	0.99909313	98981.32938	6161213.729	62.24622126
2022	Male	12	0.000920274	0.00091985	90.96543732	98846.08346	0.5	0.99908015	98891.56618	6062277.281	61.30226788
2022	Male	13	0.000923506	0.00092308	91.20008131	98755.00034	0.5	0.99907692	98800.60075	5963431.197	60.35824835
2022	Male	14	0.000915101	0.000914683	90.28779516	98664.25603	0.5	0.999085317	98709.39993	5864676.197	59.41355333
2022	Male	15	0.000894545	0.000894154	88.18068145	98575.0218	0.5	0.999105846	98619.11214	5766011.941	58.46748988
2022	Male	16	0.000862705	0.000862333	84.96649218	98488.44821	0.5	0.999137667	98530.93146	5667436.919	57.51936813
2022	Male	17	0.000821505	0.000821168	80.84064955	98405.54464	0.5	0.999178832	98445.96496	5568948.471	56.56858027
2022	Male	18	0.000773623	0.000773324	76.06183216	98327.09025	0.5	0.999226676	98365.12431	5470542.926	55.61465981
2022	Male	19	0.00072201	0.00072175	70.94009252	98255.58614	0.5	0.99927825	98289.05618	5372215.836	54.6573143
2022	Male	20	0.000669504	0.000669628	65.73544841	98185.24837	0.5	0.99933072	98218.11609	5273962.25	53.69643056
2022	Male	21	0.000618553	0.000618362	60.69365472	98122.03382	0.5	0.999381638	98152.38064	5175777.002	52.73205773
2022	Male	22	0.000571063	0.000570902	56.00075059	98063.68661	0.5	0.999429098	98091.68699	5077654.968	51.764376
2022	Male	23	0.000528387	0.000528247	51.78708464	98009.7927	0.5	0.999471753	98035.68624	497951.281	50.79365966
2022	Male	24	0.000491359	0.000491238	48.13345565	97959.83242	0.5	0.999508762	97983.89915	4881581.488	49.82024118
2022	Male	25	0.000460426	0.00046032	45.08176211	97913.22482	0.5	0.99953968	97935.7657	4783621.656	48.84448109
2022	Male	26	0.000435755	0.00043566	42.64709527	97869.36039	0.5	0.99956434	97890.68394	4685708.431	47.86674526
2022	Male	27	0.000417358	0.000417271	40.82911451	97827.62228	0.5	0.999582729	97848.03684	4587839.071	46.88739007
2022	Male	28	0.000405182	0.0004051	39.62168009	97787.39689	0.5	0.9995949	97807.20773	4490011.449	45.90675425
2022	Male	29	0.000399114	0.000399114	39.02043971	97748.07583	0.5	0.999600886	97767.58605	4392224.052	44.92515597
2022	Male	30	0.000399436	0.000399357	39.02854534	97709.05133	0.5	0.999600643	97728.56561	4294475.976	43.94289376
2022	Male	31	0.000406072	0.000405989	39.66088444	97669.70662	0.5	0.999594011	97689.53706	4196766.925	42.9602499
2022	Male	32	0.000419415	0.000419327	40.94724623	97629.40255	0.5	0.999580673	97649.87618	4099097.218	41.9774953
2022	Male	33	0.000439962	0.000439865	42.93478483	97587.46154	0.5	0.999560135	97608.92933	4001467.815	40.99485923
2022	Male	34	0.000468408	0.000468299	45.69004007	97543.14912	0.5	0.999531701	97565.99414	3903880.354	40.01271538
2022	Male	35	0.00050567	0.000505543	49.30067061	97495.65377	0.5	0.999494457	97520.30411	3806337.205	39.0312278
2022	Male	36	0.000552901	0.000552749	53.8769598	97444.06495	0.5	0.999447251	97471.00343	3708841.551	38.05071683
2022	Male	37	0.000611507	0.00061132	59.55308467	97387.34993	0.5	0.99938868	97417.12647	3611397.486	37.07148442
2022	Male	38	0.00068316	0.000682927	64.48809915	97324.32934	0.5	0.999317073	97357.57330	3514010.136	36.09385499
2022	Male	39	0.000769807	0.000769511	74.86657946	97253.652	0.5	0.999230489	97291.08529	3416685.807	35.1181796
2022	Male	40	0.000873681	0.000873333	84.89891554	97173.76925	0.5	0.9991267	97216.21871	3319432.155	34.14483919
2022	Male	41	0.000997305	0.0009969808	96.82130591	97082.90914	0.5	0.999003192	97131.3198	3222258.385	33.1742469
2022	Male	42	0.001143501	0.001142847	110.8956151	96979.05068	0.5	0.998857153	97034.49849	3125175.476	32.20684936
2022	Male	43	0.001315399	0.001314534	127.4093656	96859.89819	0.5	0.998654566	96923.60287	3028196.426	31.24312692
2022	Male	44	0.001516459	0.00151531	146.6762313	96722.85539	0.5	0.99848469	96796.19351	2931336.527	30.28359299
2022	Male	45	0.001750504	0.001748973	169.0374434	96564.99856	0.5	0.998251027	96649.51728	2834613.672	29.32879286
2022	Male	46	0.002021771	0.00201973	194.8644815	96383.04759	0.5	0.99978027	96480.47983	2738048.673	28.37930199
2022	Male	47	0.002334985	0.002332262	224.5632709	96173.33372	0.5	0.997667738	96285.61535	2641665.626	27.4357246
2022	Male	48	0.002695456	0.002691288	258.05798339	95931.76216	0.5	0.997308172	96061.05208	2545492.292	26.49869262
2022	Male	49	0.003109203	0.003104377	297.406951	95653.76877	0.5	0.998695623	95802.47225	2449560.53	25.56886553
2022	Male	50	0.003583086	0.003576678	341.5908868	95334.26985	0.5	0.996423322	95505.0653	2353906.761	24.64693107
2022	Male	51	0.00412495	0.00411646	391.7366674	94967.60608	0.5	0.99588354	95163.47441	2258572.491	23.73360688
2022	Male	52	0.004743752	0.004732527	448.5097754	94547.48285	0.5	0.995267473	94771.73774	2163604.885	22.82964243
2022	Male	53	0.005449648	0.005443839	512.6131534	94066.91221	0.5	0.994561561	94323.22797	2069057.402	21.93582055
2022	Male	54	0.006254023	0.006234527	584.8647254	93518.16409	0.5	0.993765473	93810.59645	1974990.49	21.05295739
2022	Male	55	0.00716941	0.007143802	665.9816567	92892.73865	0.5	0.992856198	93225.73173	1881472.326	20.18189926
2022	Male	56	0.008209269	0.00817571	756.741677	92181.37473	0.5	0.99182429	92559.74557	1788579.587	19.32351451
2022	Male	57	0.009387572	0.009343715	857.7810874	91374.11335	0.5	0.990656285	91803.00389	1696398.213	18.4786787
2022	Male	58	0.010718174	0.010661041	969.5707120	90460.43745	0.5	0.989338959	90945.22821	1605024.099	17.64825078
2022	Male	59	0.012213919	0.012139782	1092.284773	89429.50971	0.5	0.987860218	89975.65209	1514563.662	16.83303901
2022	Male	60	0.013885506	0.013789767	1225.680961	88270.52684	0.5	0.986210233	88883.36732	1425134.152	16.03375519
2022	Male	61	0.015740156	0.015617247	1368.971706	86973.20051	0.5	0.984382753	87657.68636	1336863.625	15.25095722
2022	Male	62	0.01778018	0.017623505	1520.709626	85528.35984	0.5	0.983276495	86288.71465	1249890.425	14.48498138
2022	Male	63	0.020001658	0.019803606	1678.712138	83928.64896	0.5	0.980196394	84768.00503	1164362.065	13.73586726
2022	Male	64	0.022393454	0.022145497	1840.053675	82169.26605	0.5	0.977854503	83089.29289	1080433.416	13.00328091
2022	Male	65	0.024936881	0.024629786	2001.151396	80248.66532	0.5	0.975370214	81249.23921	998264.1501	12.28644305
2022	Male	66	0.027602691	0.027230426	2157.9516917	8169.10823	0.5	0.972769579	79248.08782	918015.4865	11.58407113
2022	Male	67	0.030307761	0.029916468	2306.264369	75936.99647	0.5	0.970083532	77090.1286		

Table 26: Female Life Table in 2018
National Life Tables, Ghana, period expectation of life, based on data for the years 2018–2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2018	Female	0	0.000845859	0.000845249	84.52492166	99927.92488	0.147292	0.999154751	100000	7773929.025	77.73929025
2018	Female	1	0.000638625	0.000638421	63.78811253	99883.58102	0.5	0.999361579	99915.47508	7674001.1	76.80493031
2018	Female	2	0.000504462	0.000504335	50.35870918	99826.50761	0.5	0.999495665	99851.68697	7574117.519	75.85367608
2018	Female	3	0.000416625	0.000416538	41.57108409	99780.54271	0.5	0.999583462	99801.32826	7474291.012	74.89169876
2018	Female	4	0.000358628	0.000358564	35.77022518	99741.87206	0.5	0.999641436	99759.75717	7374510.469	73.92269867
2018	Female	5	0.00032024	0.000320189	31.93047669	99708.02171	0.5	0.999679811	99723.08695	7274768.597	72.94903483
2018	Female	6	0.000294972	0.000294929	29.40204906	99737.35545	0.5	0.999705071	99692.05647	7175060.575	71.97223961
2018	Female	7	0.000278566	0.000278527	27.75876267	99648.77504	0.5	0.999721473	99662.65442	7075383.22	70.99332504
2018	Female	8	0.000268096	0.00026806	26.70815451	99621.54158	0.5	0.99973194	99634.89566	6975734.445	70.01296482
2018	Female	9	0.000261451	0.000261417	26.03922508	99595.16789	0.5	0.999738583	99608.1875	6876112.903	69.03160348
2018	Female	10	0.000257037	0.000257004	25.59300443	99569.35178	0.5	0.999742996	99582.14828	6776517.735	68.04952346
2018	Female	11	0.000253627	0.000253595	25.24704285	99543.93175	0.5	0.999746405	99556.55527	6676948.383	67.06688841
2018	Female	12	0.000250286	0.000250255	24.90819644	99518.58413	0.5	0.999749745	99531.30823	6577404.452	66.08377372
2018	Female	13	0.000246345	0.000246314	24.50984022	99494.14512	0.5	0.999753686	99506.40004	6477885.598	65.10019049
2018	Female	14	0.000241387	0.000241358	24.01072168	99469.88483	0.5	0.999758642	99481.8902	6378391.452	64.11610636
2018	Female	15	0.000235238	0.000235211	23.39354918	99446.1827	0.5	0.999764789	99457.87947	6278921.568	63.1314643
2018	Female	16	0.000227938	0.000227912	22.6622819	99423.15478	0.5	0.999772088	99434.48592	6179475.385	62.14619935
2018	Female	17	0.000219695	0.000219671	21.83792254	99400.90468	0.5	0.999780329	99411.82364	6080052.23	61.16025245
2018	Female	18	0.000210841	0.000210819	20.95326883	99379.50909	0.5	0.999789181	99389.98572	5980651.325	60.17358069
2018	Female	19	0.000201768	0.000201747	20.04743477	99359.00873	0.5	0.999798253	99369.03245	5881271.816	59.18616365
2018	Female	20	0.000192884	0.000192865	19.16097624	99339.40453	0.5	0.999807135	99348.98502	5781912.808	58.1980581
2018	Female	21	0.000184576	0.000184559	18.33222925	99320.65793	0.5	0.999815441	99329.82404	5682573.403	57.20913591
2018	Female	22	0.000177187	0.000177171	17.59512927	99302.69425	0.5	0.999822829	99311.49181	5583252.745	56.21960403
2018	Female	23	0.000171007	0.000170992	16.97846219	99285.40745	0.5	0.999829008	99293.89668	5483950.051	55.22947768
2018	Female	24	0.000166279	0.000166265	16.50628296	99268.66508	0.5	0.999833735	99276.91822	5384664.643	54.23883759
2018	Female	25	0.000163212	0.000163198	16.19915017	99252.31236	0.5	0.999836802	99260.41194	5285395.978	53.24777396
2018	Female	26	0.000161996	0.000161983	16.07583878	99236.17487	0.5	0.999838017	99244.21279	5186143.666	52.25638373
2018	Female	27	0.000162823	0.000162809	16.15526674	99220.05931	0.5	0.999837191	99228.13695	5086907.491	51.26476872
2018	Female	28	0.000165906	0.000165892	16.45846116	99203.75245	0.5	0.999831408	99211.98168	4987687.432	50.27303504
2018	Female	29	0.000171499	0.000171484	17.01046768	99187.01799	0.5	0.999828516	99195.53222	4888483.679	49.28129336
2018	Female	30	0.000179916	0.000179899	17.84215634	99169.59167	0.5	0.999820101	99178.51275	4789296.661	48.28960001
2018	Female	31	0.000191545	0.000191526	18.99189376	99151.17465	0.5	0.999808474	99160.6706	4690127.07	47.29825889
2018	Female	32	0.000206867	0.000206846	20.5070368	99131.42518	0.5	0.999793154	99141.6787	4590975.895	46.30722371
2018	Female	33	0.000226467	0.000226442	22.4451605	99109.94908	0.5	0.999773558	99121.17167	4491844.47	45.31670071
2018	Female	34	0.000251043	0.000251011	24.87487102	99086.28907	0.5	0.999748899	99098.7265	4392734.521	44.32685137
2018	Female	35	0.000281405	0.000281366	27.87598182	99059.91364	0.5	0.999718634	99073.85163	4293648.232	43.33785516
2018	Female	36	0.000318476	0.000318426	31.53876515	99030.20627	0.5	0.999681574	99045.97565	4194588.318	42.34991165
2018	Female	37	0.000363265	0.000363199	35.9619536	98996.45591	0.5	0.999636801	99014.43689	4095558.112	41.36324197
2018	Female	38	0.000416836	0.000416749	41.24918972	98957.85034	0.5	0.999583251	98978.47493	3996561.656	40.37808886
2018	Female	39	0.000480255	0.000480401	47.5073847	98913.47387	0.5	0.999519896	98937.22574	3897603.806	39.39471494
2018	Female	40	0.000554524	0.000554347	54.82151463	98862.31125	0.5	0.99944563	98889.722	3798690.332	38.41339883
2018	Female	41	0.000640493	0.000640288	63.28283838	98803.25907	0.5	0.999359712	98834.90049	3698928.02	37.43442855
2018	Female	42	0.000738782	0.000738781	72.94378121	98735.14576	0.5	0.999261494	98771.61765	3601024.761	36.45809239
2018	Female	43	0.000849698	0.000849337	83.82841276	98656.75966	0.5	0.999150663	98698.67387	3502289.616	35.48466741
2018	Female	44	0.000973183	0.000972709	95.92357696	98566.88367	0.5	0.9990927291	98614.84546	3403632.856	34.51440643
2018	Female	45	0.001108806	0.001108192	109.1778654	98464.33295	0.5	0.998891808	98518.92188	3305065.972	33.54752477
2018	Female	46	0.001255807	0.001255019	123.50611115	98347.99906	0.5	0.998744981	98409.74402	3206601.639	32.5841884
2018	Female	47	0.001414132	0.001412202	138.799987	98216.83791	0.5	0.998587798	98286.2379	3108253.648	31.62450527
2018	Female	48	0.001579936	0.001578689	154.9442606	98069.96957	0.5	0.998421311	98147.43792	3010036.811	30.66852151
2018	Female	49	0.001755114	0.001755375	171.8372147	97906.57505	0.5	0.998246425	97992.49366	2911966.845	29.71622352
2018	Female	50	0.001938205	0.001936328	189.412886	97725.95	0.5	0.998063672	97820.65644	2814060.27	28.76754637
2018	Female	51	0.002129272	0.002127008	207.6624368	97527.41234	0.5	0.997872992	97631.24356	2716334.32	27.8223878
2018	Female	52	0.00232917	0.002326461	226.6521495	97310.25504	0.5	0.997673539	97423.58112	2618806.907	26.88062661
2018	Female	53	0.002539681	0.002536464	246.5361656	97073.66089	0.5	0.99746354	97196.92897	2521496.652	25.94214322
2018	Female	54	0.002763605	0.002759792	267.5629085	96816.61135	0.5	0.997240208	96950.3928	2424422.991	25.00684032
2018	Female	55	0.003004078	0.003000272	290.0747977	96537.7925	0.5	0.996999728	96682.8299	2327606.38	24.07466127
2018	Female	56	0.003268036	0.003262705	314.5011168	96235.50454	0.5	0.996737295	96392.75515	2231068.588	23.14560451
2018	Female	57	0.003559088	0.003552766	341.3435499	95907.58221	0.5	0.996447234	96078.25398	2134833.083	22.2197323
2018	Female	58	0.003884331	0.003876801	371.152976	95551.33394	0.5	0.996123199	95736.91043	2038925.501	21.29717255
2018	Female	59	0.004250524	0.00424151	404.4947842	95163.51006	0.5	0.99575849	95365.75745	1943374.167	20.37811284
2018	Female	60	0.004664315	0.004653463	441.8986756	94740.31333	0.5	0.995346537	94961.26267	1848210.657	19.46278519
2018	Female	61	0.005131537	0.005118045	483.788357	94277.46982	0.5	0.994881595	94519.364	1753470.343	18.55144035
2018	Female	62	0.00565624	0.005640289	530.387794	93770.38175	0.5	0.994359711	94035.57564	1659192.874	17.64431028
2018	Female	63	0.006239435	0.006220031	581.6051403	93214.38529	0.5	0.993779969	93505.18786	1565422.492	16.74155764
2018	Female	64	0.006877644	0.006854074	636.905104	92605.13017	0.5	0.993145926	92923.58272	1472208.107	15.84321292
2018	Female	65	0.00756147	0.007532989	695.1945664	91939.08033	0.5	0.992467011	92286.67762	1379602.976	14.94910221
2018	Female	66	0.008274662	0.008240568	754.7658395	91214.10013	0.5	0.991759432	91591.48305	1287663.896	14.0587733
2018	Female	67	0.008994332	0.008954065	813.3578268	90430.0383	0.5	0.991045935	90836.71721		

Table 27: Female Life Table in 2019
National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2019	Female	0	0.001426184	0.001424445	142.4449521	99878.36608	0.146099	0.99857555	100000	7548863.422	75.48863422
2019	Female	1	0.001076771	0.001076192	107.4658671	99803.82211	0.5	0.998923808	99857.55505	7448985.056	74.59610895
2019	Female	2	0.000850563	0.000850201	84.80765851	99707.68535	0.5	0.999149799	99750.08918	7349181.234	73.67593647
2019	Female	3	0.000702463	0.000702216	69.98655262	99630.28825	0.5	0.999297784	99665.28152	7249473.548	72.73820369
2019	Female	4	0.000604675	0.000604492	60.20456516	99565.19269	0.5	0.999395508	99595.29497	7149843.26	71.78896616
2019	Female	5	0.000539949	0.000539804	53.72940258	99508.2257	0.5	0.999460196	99535.0904	7050278.067	70.83208584
2019	Female	6	0.000497346	0.000497223	49.46437791	99456.62881	0.5	0.999502777	99481.361	6950769.842	69.87007186
2019	Female	7	0.000469684	0.000469574	46.69061676	99408.55132	0.5	0.999530426	99431.89662	6851313.213	68.90458138
2019	Female	8	0.000452031	0.000451929	44.91505591	99362.74848	0.5	0.999548071	99385.20601	6751904.662	67.93671747
2019	Female	9	0.000440826	0.000440729	43.78216447	99318.39987	0.5	0.999559271	99340.29095	6652541.913	66.96720786
2019	Female	10	0.000433384	0.000433291	43.02439229	99274.99667	0.5	0.999566709	99296.50879	6553223.513	65.99651482
2019	Female	11	0.000427635	0.000427544	42.43521101	99232.26694	0.5	0.999572456	99253.48455	6453948.517	65.02490614
2019	Female	12	0.000422002	0.000421913	41.85844185	99190.12012	0.5	0.999578087	99211.04934	6354716.25	64.05250516
2019	Female	13	0.000415356	0.00041527	41.18198419	99148.5999	0.5	0.99958473	99169.19089	6255526.13	63.07933011
2019	Female	14	0.000406997	0.000406914	40.33660468	99107.84061	0.5	0.999593086	99128.00891	6156377.53	62.10532822
2019	Female	15	0.00039663	0.000396552	39.29336599	99068.02562	0.5	0.99960348	99087.67231	6057269.689	61.13040652
2019	Female	16	0.000384321	0.000384247	38.05903307	99029.39492	0.5	0.999615753	99048.37894	5958201.663	60.15445914
2019	Female	17	0.000370424	0.000370355	36.66897288	98991.98542	0.5	0.999629645	99010.31991	5859172.314	59.17738999
2019	Female	18	0.000355494	0.000355431	35.17831776	98956.06178	0.5	0.999644569	98973.65093	5760180.329	58.19912951
2019	Female	19	0.000340196	0.000340138	33.65275476	98921.64624	0.5	0.999659862	98938.47262	5661224.267	57.21964487
2019	Female	20	0.000325217	0.000325165	32.16034126	98888.73969	0.5	0.999674835	98904.81986	5562302.621	56.2389435
2019	Female	21	0.000311121	0.000311161	30.76536425	98857.27684	0.5	0.999688839	98872.65952	5463413.881	55.25707417
2019	Female	22	0.000298751	0.000298706	29.52469011	98827.13181	0.5	0.999701294	98841.89416	5364556.604	54.27411777
2019	Female	23	0.000288331	0.000288289	28.48651777	97989.12621	0.5	0.999711711	98812.36947	5265729.472	53.29018523
2019	Female	24	0.000280359	0.000280302	27.69108985	98770.0374	0.5	0.99971968	98783.88295	5166931.346	52.30540845
2019	Female	25	0.000275188	0.000275151	27.17276962	98742.60547	0.5	0.99972485	98756.19186	5068161.309	51.31993461
2019	Female	26	0.000273138	0.0002731	26.96291658	98715.53763	0.5	0.9997269	98729.01909	4969418.703	50.33392157
2019	Female	27	0.000274532	0.000274494	27.09311669	98688.50961	0.5	0.999725506	98702.05617	4870703.166	49.34753494
2019	Female	28	0.000279793	0.000279691	27.59847515	98661.16382	0.5	0.999720309	98674.96306	4772014.656	48.36094697
2019	Female	29	0.000289161	0.000289119	28.52080594	98633.10418	0.5	0.999710881	98647.36458	4673353.492	47.37433698
2019	Female	30	0.000303352	0.000303306	29.91166453	98603.88794	0.5	0.999696694	98618.84377	4574720.388	46.38789316
2019	Female	31	0.000322996	0.000322907	31.83509669	98573.01456	0.5	0.999677093	98588.93211	4476116.5	45.40181544
2019	Female	32	0.000348794	0.000348733	34.37015234	98539.91193	0.5	0.999651267	98557.09701	4377543.485	44.41631925
2019	Female	33	0.000381842	0.000381769	37.61289003	98503.92041	0.5	0.999618231	98522.72686	4279003.573	43.43163968
2019	Female	34	0.000423277	0.000423188	41.67769463	98464.27512	0.5	0.999576812	98485.11397	4180499.653	42.4480359
2019	Female	35	0.000474471	0.000474359	46.69750754	98420.08752	0.5	0.999525641	98443.46327	4082035.378	41.46579531
2019	Female	36	0.000536976	0.000536832	52.82248706	98370.32752	0.5	0.999463168	98396.73876	3983615.29	40.48523702
2019	Female	37	0.000612493	0.000612306	60.21655055	98313.808	0.5	0.999387694	98343.91628	3885244.963	39.50671389
2019	Female	38	0.000702818	0.000702571	69.05129121	98249.17408	0.5	0.999274729	98283.69793	3786931.155	38.53061256
2019	Female	39	0.000809748	0.000809421	79.49661929	98174.89996	0.5	0.999190579	98214.64844	3688681.981	37.55735055
2019	Female	40	0.000934971	0.000934534	91.71061707	98089.29617	0.5	0.999065466	98135.15147	3590507.081	36.58736984
2019	Female	41	0.001079922	0.001079339	105.8221332	97990.52979	0.5	0.999820661	98043.44086	3492417.785	35.62112625
2019	Female	42	0.001245645	0.001244869	121.9159534	97876.65895	0.5	0.998755131	97937.61872	3394427.255	34.65907482
2019	Female	43	0.001432657	0.001431631	140.0360009	97745.68117	0.5	0.998568369	97815.69917	3296550.596	33.70165141
2019	Female	44	0.001640862	0.001639517	160.1409025	97595.59272	0.5	0.998360483	97675.66317	3198804.915	32.74925208
2019	Female	45	0.001869534	0.001867788	182.1383336	97424.4531	0.5	0.998132212	97515.52227	3101209.322	31.8022121
2019	Female	46	0.002117389	0.002115155	205.8746922	97230.44659	0.5	0.99788485	97333.38393	3003784.869	30.8607874
2019	Female	47	0.002382765	0.00237993	231.1566292	97011.93093	0.5	0.99762007	97127.50924	2906554.422	29.92514114
2019	Female	48	0.002663896	0.002660352	277.7884176	96767.46434	0.5	0.997339648	96896.35261	2809542.491	28.99533796
2019	Female	49	0.00295926	0.002954888	285.5561291	96495.79613	0.5	0.997045112	96638.57149	2712775.028	28.07134781
2019	Female	50	0.003267965	0.003262634	314.3645884	96195.83577	0.5	0.996737366	96353.01807	2616279.232	27.15305949
2019	Female	51	0.00359012	0.003583687	344.172485	95866.56723	0.5	0.996416313	96038.65348	2520083.396	26.2403033
2019	Female	52	0.003927163	0.003919467	375.0713681	95506.94531	0.5	0.996080533	95694.48099	2424216.829	25.33288026
2019	Female	53	0.004282101	0.004279535	407.2953451	95115.76195	0.5	0.99572047	95319.40962	2328709.884	24.43059491
2019	Female	54	0.004659655	0.004648824	441.2297126	94691.49942	0.5	0.995351176	94912.11428	2233594.122	23.53328802
2019	Female	55	0.005060624	0.005053492	477.4079008	94232.18062	0.5	0.994945608	94470.88457	2138902.622	22.64086583
2019	Female	56	0.005510165	0.005495026	516.4965593	93735.22839	0.5	0.994504794	93933.47667	2044670.442	21.75332283
2019	Female	57	0.006000091	0.00598295	559.2680762	93197.34607	0.5	0.99401705	93476.98011	1950935.213	20.87075568
2019	Female	58	0.006549285	0.006527909	606.5583572	92614.43285	0.5	0.993472091	92917.71203	1857737.867	19.99336646
2019	Female	59	0.007166716	0.007141127	659.2056626	91981.55084	0.5	0.992858873	92311.15367	1765123.434	19.12145352
2019	Female	60	0.0078644	0.007833597	717.9644253	91292.9658	0.5	0.992166403	91651.94801	1673141.883	18.25538813
2019	Female	61	0.008652173	0.008614905	783.3875992	90542.28979	0.5	0.991385905	90393.98359	1581848.918	17.39557485
2019	Female	62	0.009536863	0.009491603	855.6736767	89722.75915	0.5	0.990508397	90150.55959	1491306.628	16.54239344
2019	Female	63	0.010520176	0.010465129	934.4828736	88827.68087	0.5	0.989534871	89294.92231	1401583.869	15.69612059
2019	Female	64	0.011596246	0.011529397	1018.742573	87851.06815	0.5	0.988470603	88360.43944	1312756.188	14.85683182
2019	Female	65	0.01274923	0.012668473	1106.48592	86788.45391	0.5	0.987331527	87341.69687	1224905.12	14.0242881
2019	Female	66	0.013951727	0.013855076	1194.795432	85637.81323	0.5	0.986144924	86235.21095	1138116.666	13.19781854
2019	Female	67	0.015165148	0.015051023	1279.945234	84400.4429	0.5	0.984948977	85040.41551		

Table 28: Female Life Table in 2020
National Life Tables, Ghana, period expectation of life, based on data for the years 2018-2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2020	Female	0	0.001649371	0.00164705	164.7049822	99859.28267	0.14564	0.99835295	100000	7468395.966	74.86395966
2020	Female	1	0.001245277	0.001244502	124.245256	99773.17239	0.5	0.998755498	99835.29502	7368536.683	73.80693052
2020	Female	2	0.000983669	0.000983186	98.03447743	99662.03252	0.5	0.999016814	99711.04976	7268763.511	72.89827485
2020	Female	3	0.000812392	0.000812063	80.8920028	99572.56928	0.5	0.999187937	99613.01528	7169101.478	71.96952585
2020	Female	4	0.000699302	0.000699057	69.57864858	99497.33396	0.5	0.999300943	99532.12328	7069528.909	71.02761075
2020	Female	5	0.000624447	0.000624252	62.08971683	99431.49977	0.5	0.999375748	99462.54463	6970031.575	70.07694807
2020	Female	6	0.000575177	0.000575012	57.15641344	99371.87671	0.5	0.999424988	99400.45492	6870600.075	69.12040877
2020	Female	7	0.000543186	0.000543038	53.94723202	99316.32489	0.5	0.999456962	99343.2985	6771228.199	68.159889
2020	Female	8	0.00052277	0.000522634	51.89197239	99263.40528	0.5	0.999477366	99289.35127	6671911.874	67.19665088
2020	Female	9	0.000509812	0.000509682	50.57956858	99212.16951	0.5	0.999490318	99237.4593	6572648.468	66.23152704
2020	Female	10	0.000501206	0.00050108	49.70057175	99162.02944	0.5	0.99948982	99186.87973	6473436.299	65.26504631
2020	Female	11	0.000494557	0.000494434	49.016838	99112.67074	0.5	0.999505566	99137.17916	6374274.27	64.29751506
2020	Female	12	0.000488042	0.000487923	48.34739867	99063.98862	0.5	0.999512077	99088.16232	6275161.599	63.32907435
2020	Female	13	0.000480356	0.000480241	47.56295911	99016.03344	0.5	0.999519759	99039.81492	6176097.61	62.35974507
2020	Female	14	0.000470689	0.000470578	46.58359403	98968.96017	0.5	0.999529422	98992.25196	6077081.577	61.38946692
2020	Female	15	0.0004587	0.000458594	45.37593406	98922.9804	0.5	0.999541046	98945.66837	5978112.617	60.41813366
2020	Female	16	0.000444464	0.000444365	43.94784223	98878.31851	0.5	0.999555635	98900.29243	5879189.636	59.44562439
2020	Female	17	0.000428392	0.0004283	42.34019988	98835.17449	0.5	0.9995717	98856.34459	5780311.318	58.47182942
2020	Female	18	0.000411126	0.000411042	40.61669277	98793.69605	0.5	0.999588958	98814.00439	5681476.143	57.49666941
2020	Female	19	0.000393434	0.000393357	38.85317104	98753.96111	0.5	0.999606643	98773.3877	5582682.447	56.52010706
2020	Female	20	0.000376111	0.000376041	37.12819922	98715.97043	0.5	0.999623959	98734.53453	5483928.486	55.54215161
2020	Female	21	0.000359912	0.000359847	35.51596926	98679.64834	0.5	0.999640153	98697.40633	5385212.516	54.56285748
2020	Female	22	0.000345503	0.000345443	34.08209089	98644.84931	0.5	0.999654557	98661.89036	5286532.867	53.58231885
2020	Female	23	0.000333452	0.000333396	32.8821568	98611.36719	0.5	0.999666004	98627.80827	5187888.018	52.60066212
2020	Female	24	0.000324233	0.000324181	31.96256732	98578.94483	0.5	0.999675819	98594.92611	5089276.651	51.61803808
2020	Female	25	0.000318253	0.000318202	31.36293046	98547.28208	0.5	0.999681798	98562.96354	4990697.706	50.63461493
2020	Female	26	0.000315881	0.000315831	31.11938197	98516.04092	0.5	0.999684169	98531.60061	4892150.424	49.65057295
2020	Female	27	0.000317494	0.000317443	31.2683131	98484.84708	0.5	0.999682557	98500.48123	4793634.383	48.66610115
2020	Female	28	0.000323505	0.000323453	31.85016871	98453.28783	0.5	0.999676547	98469.21292	4695149.536	47.68139601
2020	Female	29	0.000334412	0.000334356	32.91312857	98420.90619	0.5	0.999665644	98437.36275	4596696.248	46.69666191
2020	Female	30	0.000350824	0.000350762	34.51658053	98387.19133	0.5	0.999649238	98404.44962	4498275.342	45.71211321
2020	Female	31	0.0003735	0.00037343	36.73432582	98351.56588	0.5	0.99962657	98369.93304	4399888.15	44.72797749
2020	Female	32	0.000403378	0.000403296	39.65742671	98313.37	0.5	0.999596704	98333.19872	4301536.585	43.74449973
2020	Female	33	0.0004411597	0.000441499	43.39652452	98271.84303	0.5	0.999558501	98293.54129	4203223.215	42.76194712
2020	Female	34	0.000489517	0.000489397	48.08333419	98226.1031	0.5	0.999510603	98250.14476	4104951.372	41.78061398
2020	Female	35	0.000548722	0.000548572	53.8708814	98175.12599	0.5	0.999451428	98202.06143	4006725.268	40.80082648
2020	Female	36	0.000621008	0.000620816	60.931919	98117.72459	0.5	0.999379184	98148.19055	3908550.142	39.82294651
2020	Female	37	0.000708344	0.000708093	69.45488954	98052.53118	0.5	0.999291907	98087.25863	3810432.418	38.84737397
2020	Female	38	0.000818203	0.000818247	79.63684768	97977.98532	0.5	0.999187527	98017.80374	3712379.887	37.87454672
2020	Female	39	0.000936468	0.000936029	91.67298827	97892.3304	0.5	0.999063971	97938.16689	3614401.901	36.90493723
2020	Female	40	0.001081286	0.001080702	105.7428937	97793.62246	0.5	0.998919298	97846.4939	3516509.571	35.93904524
2020	Female	41	0.001248921	0.001248142	121.9943234	97679.75385	0.5	0.998751858	97740.75101	3418715.949	34.97738572
2020	Female	42	0.001440578	0.001439541	140.562649	97548.49356	0.5	0.99860459	97618.75669	3321036.195	34.02047217
2020	Female	43	0.001656856	0.001655485	161.373711	97397.54358	0.5	0.998344515	97478.23044	3223487.701	33.06879584
2020	Female	44	0.001897644	0.0018955845	184.497687	97224.60788	0.5	0.998104155	97316.85673	3126090.158	32.12280239
2020	Female	45	0.002162101	0.002159767	209.7832156	97087.47473	0.5	0.997840233	97017.3235904	3028865.55	31.1828682
2020	Female	46	0.002448744	0.002445749	237.0483175	96804.05167	0.5	0.997554251	96922.57582	2931838.082	30.24927946
2020	Female	47	0.002755649	0.002751857	266.0647654	96552.49512	0.5	0.997248143	96685.52751	2835034.031	29.32221713
2020	Female	48	0.0030080774	0.0030076036	296.5897219	96271.16788	0.5	0.996923964	96419.46274	2738481.535	28.40175062
2020	Female	49	0.00342236	0.003416514	328.4051617	95958.67044	0.5	0.996583486	96122.87302	2642210.368	27.48784222
2020	Female	50	0.003779375	0.003772247	361.360376	95613.78767	0.5	0.996227753	95794.46786	2546251.097	26.58036267
2020	Female	51	0.004151945	0.004143344	395.4121843	95235.40139	0.5	0.995856656	95433.10748	2450637.909	25.67911676
2020	Female	52	0.00451733	0.004513443	430.6578887	94822.36635	0.5	0.995468557	95307.69553	2355402.508	24.78387655
2020	Female	53	0.004952216	0.004939984	467.3572963	94373.35876	0.5	0.995060016	94607.03741	2260580.142	23.89441847
2020	Female	54	0.005388854	0.005374373	505.9417677	93886.70923	0.5	0.994625627	94139.68011	2166206.783	23.01056027
2020	Female	55	0.005859128	0.005842014	547.0096025	93360.23354	0.5	0.994157986	93633.73835	2072320.074	22.13219413
2020	Female	56	0.006372462	0.006352222	591.3075942	92791.07495	0.5	0.993647778	93086.72874	197895.84	21.25931233
2020	Female	57	0.006933995	0.006915996	639.6979906	92175.57215	0.5	0.993084004	92495.42115	1886168.765	20.39202311
2020	Female	58	0.007574197	0.007545621	693.108445	91509.16894	0.5	0.992454379	91855.72316	1793993.193	19.53055435
2020	Female	59	0.00828825	0.008254045	752.4602824	90786.38457	0.5	0.991745955	91162.61471	1702484.024	18.67524346
2020	Female	60	0.009095117	0.009053943	818.568406	90000.87023	0.5	0.990946057	90410.15443	1611697.64	17.8265113
2020	Female	61	0.01000617	0.009956358	892.0058631	89145.58309	0.5	0.990043642	89591.58602	1521696.769	16.98481785
2020	Female	62	0.011029307	0.010968817	972.9294996	88213.11541	0.5	0.989031883	88699.58016	1432551.186	16.15059715
2020	Female	63	0.012166501	0.012092936	1060.872795	87196.21426	0.5	0.987907064	87726.65066	1344338.071	15.32416957
2020	Female	64	0.013410966	0.013321638	1154.530138	86088.5128	0.5	0.986678362	86665.77787	1257141.857	14.50563172
2020	Female	65	0.014744383	0.01463648	1251.583663	84885.4559	0.5	0.98536352	85511.24773	1171053.344	13.69472876
2020	Female	66	0.016135062	0.016005934	1348.6546049	83585.33676	0.5	0.983994066	84259.66406	1086167.888	12.89072179
2020	Female	67	0.017538374	0.017385913	1441.483636	82190.26764	0.5	0.982614087	82911.00946		

Table 29: Female Life Table in 2021
National Life Tables, Ghana, period expectation of life, based on data for the years 2018–2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2021	Female	0	0.001308356	0.001306896	130.6896213	99888.43563	0.146341	0.998693104	100000	7592651.122	75.92651122
2021	Female	1	0.00098781	0.000987323	98.60325027	99820.00875	0.5	0.999012677	99869.31038	7492762.687	75.02567764
2021	Female	2	0.000780291	0.000779987	77.8198406	99731.79721	0.5	0.999220013	99770.70713	7392942.678	74.09933126
2021	Female	3	0.000644427	0.000644219	64.22405599	99660.77526	0.5	0.999355781	99692.88729	7293210.881	73.15678259
2021	Female	4	0.000554718	0.000554564	55.25047336	99601.038	0.5	0.999445436	99628.66323	7193550.106	72.20361964
2021	Female	5	0.00049534	0.000495217	49.31046823	99548.75752	0.5	0.999504783	99573.41276	7093949.068	71.24340596
2021	Female	6	0.000456257	0.000456152	45.3981626	99501.40321	0.5	0.999543848	99524.10229	6994400.31	70.27845667
2021	Female	7	0.00043088	0.000430787	42.85413015	99457.27706	0.5	0.999569213	99478.70413	6894898.907	69.31030081
2021	Female	8	0.000414685	0.000414599	41.22603371	99415.23698	0.5	0.999585401	99435.85	6795441.63	68.33995616
2021	Female	9	0.000404406	0.000404324	40.18767261	99374.53013	0.5	0.999595676	99394.62396	6696026.393	67.36809423
2021	Female	10	0.000397579	0.0003975	39.49339881	99334.68959	0.5	0.9996025	99354.43629	6596651.863	66.39514156
2021	Female	11	0.000392305	0.000392228	38.95409546	99295.46584	0.5	0.999607772	99314.94289	6497317.173	65.42134531
2021	Female	12	0.000387137	0.000387062	38.42598943	99256.77758	0.5	0.999612938	99275.9888	6398021.707	64.44681926
2021	Female	13	0.00038104	0.000380968	37.80630998	99218.65965	0.5	0.999619032	99237.56281	6298764.931	63.47158025
2021	Female	14	0.000373372	0.000373302	37.03148392	99181.24076	0.5	0.999626698	99199.7565	6199546.272	62.49557953
2021	Female	15	0.000363861	0.000363795	36.07492421	99144.68755	0.5	0.999632605	99162.72501	6100365.031	61.51873126
2021	Female	16	0.000352569	0.000352507	34.94282031	99109.17868	0.5	0.999647493	99126.65009	6001220.343	60.54093766
2021	Female	17	0.00033982	0.000339762	33.6676257	99074.87346	0.5	0.999660238	99091.70727	5902111.165	59.56210996
2021	Female	18	0.000326124	0.000326071	32.29994893	99041.88967	0.5	0.999673929	99058.03964	5803036.291	58.58218386
2021	Female	19	0.00031209	0.000312041	30.90009892	99010.28964	0.5	0.999687959	99025.73969	5703994.402	57.60112895
2021	Female	20	0.000298349	0.000298304	29.53057038	99890.07431	0.5	0.999701696	98994.83936	5604984.112	56.61895241
2021	Female	21	0.000285498	0.000285458	28.2504042	98951.18382	0.5	0.999714542	98965.30903	5506004.038	55.63569792
2021	Female	22	0.000274069	0.000274031	27.11183393	98923.5027	0.5	0.999725969	98937.05862	5407052.854	54.65144132
2021	Female	23	0.000264509	0.000264474	26.15913889	98896.86722	0.5	0.999735526	98909.94679	5308129.351	53.66628457
2021	Female	24	0.000257197	0.000257163	25.42929566	98871.073	0.5	0.999742837	98883.78765	5209232.484	52.68034941
2021	Female	25	0.000252452	0.000252421	24.95388423	98845.58814	0.5	0.999747579	98858.35835	5110361.411	51.69377174
2021	Female	26	0.000250571	0.00025054	24.76172832	98821.0236	0.5	0.99974946	98833.40447	501151.53	50.70669736
2021	Female	27	0.00025185	0.000251819	24.88186212	98796.20181	0.5	0.999748181	98808.64274	4912694.506	49.7192793
2021	Female	28	0.000256619	0.000256586	25.34655514	98771.08576	0.5	0.999743414	98783.76088	4813898.304	48.73167676
2021	Female	29	0.000265271	0.000265236	26.19424647	98745.3172	0.5	0.999734764	98758.41432	4715127.217	47.74405552
2021	Female	30	0.000278289	0.000278251	27.47231593	98718.48392	0.5	0.999721749	98732.22008	4616381.899	46.75658965
2021	Female	31	0.000296277	0.000296233	29.23964532	98690.12794	0.5	0.999703767	98704.74776	4517663.415	45.76946416
2021	Female	32	0.000319978	0.000319926	31.56889897	98659.72367	0.5	0.999680074	98675.50811	4418973.287	44.78287847
2021	Female	33	0.000350295	0.000350233	34.54838814	98626.66502	0.5	0.999649767	98643.93922	4230313.564	43.79705026
2021	Female	34	0.000388307	0.000388232	38.28238688	98590.24918	0.5	0.999611768	98609.39083	4221686.899	42.81221964
2021	Female	35	0.000435271	0.000435177	42.89585573	98549.65961	0.5	0.999564823	98571.10754	4123096.65	41.82865296
2021	Female	36	0.000492612	0.000492491	48.52426998	98503.94957	0.5	0.999507509	98528.21169	4024546.99	40.84664606
2021	Female	37	0.00056189	0.000561733	53.51924891	98452.02783	0.5	0.999438267	98479.68746	3926043.04	39.8665262
2021	Female	38	0.000644545	0.000644545	63.43892297	98392.64875	0.5	0.999355455	98424.36821	3827591.013	38.88865209
2021	Female	39	0.000724849	0.000724753	73.0410506	98324.40921	0.5	0.999257427	98360.92929	3729198.364	37.91341126
2021	Female	40	0.000857725	0.000857358	84.2678757	98245.7552	0.5	0.999142642	98287.88914	3630873.955	36.94121409
2021	Female	41	0.000990701	0.000990211	97.24226982	98155.00013	0.5	0.999009789	98203.62126	3532628.199	35.97248405
2021	Female	42	0.001142732	0.001142028	112.0453033	98050.35634	0.5	0.99885792	98106.37899	3434473.199	35.0076441
2021	Female	43	0.001314294	0.001313434	128.7087399	97929.97932	0.5	0.99868657	97994.33369	3336422.843	34.04709964
2021	Female	44	0.001505297	0.001504165	147.2060788	97792.02191	0.5	0.998495835	97865.62495	3238492.864	33.09121937
2021	Female	45	0.001715077	0.001713608	167.4510219	97634.69336	0.5	0.998286392	97718.41887	3140700.842	32.1403158
2021	Female	46	0.001942455	0.001940457	189.3044941	97456.31356	0.5	0.998059493	97550.96785	3043066.148	31.19462795
2021	Female	47	0.002185906	0.002183519	212.5910799	97255.36781	0.5	0.997816481	97361.66335	2945609.833	30.25430885
2021	Female	48	0.002444381	0.002440828	237.1241378	97030.5102	0.5	0.99759172	97149.07227	2848354.465	29.31942013
2021	Female	49	0.002714772	0.002711092	262.7371982	96780.57954	0.5	0.997288908	96911.94813	2751323.955	28.38993548
2021	Female	50	0.002997972	0.002993485	289.3179631	96504.55195	0.5	0.997006515	96649.21094	2654543.375	27.46575321
2021	Female	51	0.003293512	0.003288097	316.8406857	96201.47263	0.5	0.996711903	96359.89297	2558038.823	26.54671715
2021	Female	52	0.003602709	0.003596231	345.3930148	95870.35578	0.5	0.996403769	96043.05229	2461837.351	25.63264382
2021	Female	53	0.003928323	0.003920622	375.19439	95510.06208	0.5	0.996079378	95697.65927	2365966.995	24.72335283
2021	Female	54	0.004274684	0.004265567	406.6043577	95119.1627	0.5	0.995734433	95322.46488	2270456.933	23.81869726
2021	Female	55	0.004647727	0.004636951	421.602322	94695.80041	0.5	0.995363049	94915.86052	2175337.77	22.91859082
2021	Female	56	0.005054926	0.005042183	476.3639298	94237.55833	0.5	0.994597817	94475.74029	2080641.97	22.02302901
2021	Female	57	0.005505119	0.005490008	516.057306	93741.34771	0.5	0.994509992	93999.37636	1986404.411	21.13210202
2021	Female	58	0.006008197	0.005990202	559.9839611	93203.32708	0.5	0.994009798	93483.31906	1892663.064	20.24597771
2021	Female	59	0.006574617	0.006553075	608.933579	92618.86831	0.5	0.993446925	92923.3351	1799459.737	19.36499303
2021	Female	60	0.00721466	0.007188728	663.623103	91982.58997	0.5	0.992811272	92314.40152	1706840.868	18.4894322
2021	Female	61	0.007937349	0.007909573	724.5885516	91288.48414	0.5	0.992094027	91650.77841	161458.278	17.61968972
2021	Female	62	0.008748947	0.008710842	792.0436767	90530.16802	0.5	0.991289158	90926.18986	1523569.794	16.7561161
2021	Female	63	0.009651021	0.009604674	865.7090803	89701.29165	0.5	0.990395326	90134.14619	1433039.626	15.8989649
2021	Female	64	0.010638188	0.010581902	944.6298447	88796.12218	0.5	0.989418098	89268.4371	1343338.334	15.04830126
2021	Female	65	0.011695915	0.011627915	1027.02174	87810.29639	0.5	0.988372085	88323.80726	1254542.212	14.20389645
2021	Female	66	0.012790965	0.012717678	1110.212374	86741.67933	0.5	0.987282327	87296.78552	1166731.916	13.36511887
2021	Female	67	0.013912235	0.013816129	1190.764788	85591.19075	0.5	0.986183871	86186.57315	1079990.237	

Table 30: Female Life Table in 2022
 National Life Tables, Ghana, period expectation of life, based on data for the years 2018–2020

Year	Sex	age	mx	qx	dx	Lx	ax	px	lx	Tx	ex
2022	Female	0	0.000711866	0.000711435	71.14345572	99939.35496	0.147567	0.999288565	100000	7829443.462	78.29443462
2022	Female	1	0.00053746	0.000537316	53.69333501	99902.00988	0.5	0.999462684	99928.85654	7729504.107	77.35007059
2022	Female	2	0.00042455	0.00042446	42.39303799	99853.96669	0.5	0.99957554	99875.16321	7629602.098	76.39138553
2022	Female	3	0.000350628	0.000350566	34.9979806	99815.27118	0.5	0.999649434	99832.77017	7529748.131	75.42361209
2022	Female	4	0.000301818	0.000301772	30.11618652	99782.7141	0.5	0.999698228	99797.77219	7429932.86	74.44988697
2022	Female	5	0.000269511	0.000269474	26.88481539	99754.2136	0.5	0.999730526	99767.656	7330150.146	73.47220972
2022	Female	6	0.000248246	0.000248215	24.75713682	99728.39262	0.5	0.999751785	99740.77119	7230395.932	72.49187916
2022	Female	7	0.000234438	0.000234411	23.37451732	99704.32679	0.5	0.999765589	99716.01405	7130667.539	71.50975304
2022	Female	8	0.000225627	0.000225602	22.49081701	99681.39413	0.5	0.999774398	99692.63953	7030963.213	70.5264024
2022	Female	9	0.000220034	0.00022001	21.92843427	99659.1845	0.5	0.99977999	99670.14872	6931281.818	69.54220404
2022	Female	10	0.00021632	0.000216296	21.55354322	99637.44351	0.5	0.999783704	99648.22028	6831622.634	68.55739736
2022	Female	11	0.00021345	0.000213427	21.26304636	99616.03522	0.5	0.999786573	99626.66674	6731985.19	67.57212111
2022	Female	12	0.000210638	0.000210616	20.97850738	99594.91444	0.5	0.999789384	99605.40369	6632369.155	66.58643918
2022	Female	13	0.000207321	0.0002073	20.64381006	99574.10328	0.5	0.9997927	99584.42519	6532774.241	65.60036099
2022	Female	14	0.000203149	0.000203128	20.22420118	99553.66928	0.5	0.999796872	99563.78138	6433200.137	64.61385906
2022	Female	15	0.000197974	0.000197955	19.70510142	99533.70462	0.5	0.999803425	99543.55717	6333646.468	63.62685053
2022	Female	16	0.00019183	0.000191812	19.08983296	99514.30716	0.5	0.999801888	99523.85207	6234112.764	62.63938376
2022	Female	17	0.000184893	0.000184876	18.39607663	99495.56462	0.5	0.999815124	99504.76224	6134598.456	61.65130511
2022	Female	18	0.000177442	0.000177426	17.65145393	99477.54044	0.5	0.999825274	99486.36616	6035102.892	60.66261263
2022	Female	19	0.000169806	0.000169791	16.88891308	99460.27025	0.5	0.999830209	99468.71471	5935625.352	59.67328892
2022	Female	20	0.000162329	0.000162316	16.14262282	99443.75449	0.5	0.999837684	99451.8258	5836165.082	58.68333773
2022	Female	21	0.000155337	0.000155325	15.44488684	99427.96073	0.5	0.999844675	99435.68317	5736721.327	57.69278335
2022	Female	22	0.000149119	0.000149108	14.82430552	99412.82613	0.5	0.999850892	99420.23829	5637293.366	56.70166823
2022	Female	23	0.000143917	0.000143907	14.305143683	99398.26141	0.5	0.999856093	99405.41398	5537880.54	55.71004957
2022	Female	24	0.000139939	0.000139929	13.90768227	99384.155	0.5	0.999860071	99391.10884	5438482.279	54.71799583
2022	Female	25	0.000137357	0.000137348	13.6492579	99370.37653	0.5	0.999862652	99377.20116	5339098.124	53.72558355
2022	Female	26	0.000136334	0.000136325	13.54570574	99356.77904	0.5	0.999863675	99363.5519	5239727.747	52.73289498
2022	Female	27	0.00013703	0.00013702	13.61298297	99343.1997	0.5	0.99986298	99350.00619	5140370.968	51.74001659
2022	Female	28	0.000139625	0.000139615	13.8688261	99329.45588	0.5	0.999860385	99336.39321	5041027.769	50.74703848
2022	Female	29	0.000144332	0.000144321	14.33436095	99315.3572	0.5	0.999855679	99322.52438	4941698.31	49.75405469
2022	Female	30	0.000151415	0.000151404	15.03562587	99300.67221	0.5	0.999848596	99308.19002	4842382.953	48.76116412
2022	Female	31	0.000161202	0.000161189	16.0049831	99285.1519	0.5	0.999838811	99293.1544	4743082.28	47.76847215
2022	Female	32	0.000174097	0.000174082	17.28238051	99288.50822	0.5	0.999825918	99277.14941	4643797.128	46.77609254
2022	Female	33	0.000190593	0.000190574	18.91639061	99250.40884	0.5	0.999809426	99259.86703	4544528.62	45.78414979
2022	Female	34	0.000211275	0.000211253	20.96490124	99230.46819	0.5	0.999788747	99240.95064	4445278.211	44.79278143
2022	Female	35	0.000236828	0.0002368	23.49527167	99208.2381	0.5	0.9997632	99219.98574	4346047.743	43.80214037
2022	Female	36	0.000268026	0.00026799	26.58371169	99183.19861	0.5	0.9997201	99196.49047	4246839.505	42.81239674
2022	Female	37	0.00030572	0.000305673	30.31361005	99154.74995	0.5	0.999694327	99169.90676	4147656.306	41.8237391
2022	Female	38	0.000350805	0.000350743	34.7255788	99122.20687	0.5	0.999694257	99139.59315	4048501.556	40.83637453
2022	Female	39	0.000404178	0.000404096	40.04791068	99084.79663	0.5	0.999595904	99104.82059	3949379.35	39.85052721
2022	Female	40	0.000466682	0.000466573	46.22093196	99041.66221	0.5	0.999533427	99064.77268	3850294.553	38.86643505
2022	Female	41	0.000539033	0.000538888	53.35986508	98991.87181	0.5	0.999461112	99018.55175	3751252.891	37.88434414
2022	Female	42	0.000621752	0.000621559	61.51265715	98934.43555	0.5	0.999378441	98965.19188	3652261.019	36.90450096
2022	Female	43	0.000715097	0.000714841	70.70043677	98868.32901	0.5	0.999285159	98903.67922	3553326.583	35.92714256
2022	Female	44	0.000819021	0.000818685	80.91311466	98792.52233	0.5	0.999181315	98832.97879	3454458.254	34.95248546
2022	Female	45	0.00093316	0.000932725	92.1085118	98706.01142	0.5	0.999067275	98752.06567	3355665.732	33.98071432
2022	Female	46	0.001056875	0.001056316	104.2161316	98607.8491	0.5	0.999843684	98659.95716	3256959.721	33.01197177
2022	Female	47	0.001189334	0.001188628	117.1460712	98497.16799	0.5	0.998811372	98555.74103	3158351.872	32.04635102
2022	Female	48	0.001329658	0.001328775	130.8027116	98373.1936	0.5	0.998671225	98438.59496	3059854.704	31.0838925
2022	Female	49	0.001477086	0.001475996	145.10193	98235.24128	0.5	0.998524004	98307.79225	2961481.51	30.12458568
2022	Female	50	0.001631173	0.001629844	159.9898823	98082.69538	0.5	0.998370156	98162.69032	2863246.269	29.16837609
2022	Female	51	0.001791974	0.00179037	175.4610993	97914.96988	0.5	0.99820963	98002.70043	2765163.573	28.21517735
2022	Female	52	0.001960206	0.001958287	191.5737899	97731.45244	0.5	0.998041713	97827.23934	2667248.604	27.26488677
2022	Female	53	0.00213737	0.002135088	208.46076761	97531.43516	0.5	0.997864912	97635.66555	2569517.151	26.31704294
2022	Female	54	0.002325822	0.002323121	226.3351613	97314.03719	0.5	0.997676879	97427.20477	2471985.716	25.37264332
2022	Female	55	0.002528792	0.002525599	245.4904026	97078.12441	0.5	0.997474401	97200.86961	2374671.679	24.43056002
2022	Female	56	0.002750346	0.002746569	266.2946618	96822.23187	0.5	0.997253441	96955.37921	2277593.554	23.49115204
2022	Female	57	0.002995293	0.002990813	289.179019	96544.49503	0.5	0.997009187	96689.08454	2180771.322	22.55447275
2022	Female	58	0.003269013	0.003263679	314.6183362	96242.59636	0.5	0.996736321	96399.90552	2084226.827	21.62063143
2022	Female	59	0.003577198	0.003570811	343.1024252	95913.73598	0.5	0.996429189	96085.28719	1987984.231	20.6897881
2022	Female	60	0.00392544	0.003917751	375.0940372	95554.63774	0.5	0.996082249	95742.18476	1892070.495	19.76214037
2022	Female	61	0.00431865	0.004309345	410.9696005	95161.6059	0.5	0.995690655	95367.09073	1796515.857	18.83790146
2022	Female	62	0.004760234	0.004748931	450.9400966	94730.65102	0.5	0.995250169	94956.12107	1701354.251	17.91726781
2022	Female	63	0.005251046	0.005237295	494.9515233	94257.70521	0.5	0.994762705	94505.18097	1606623.6	17.00037589
2022	Female	64	0.005788155	0.005771452	542.5755699	93738.94166	0.5	0.994228548	94010.22945	1512365.895	16.08724821
2022	Female	65	0.006363656	0.006343473	592.9094952	93171.19913	0.5	0.993656527	93467.65388	1418626.954	15.17773149
2022	Female	66	0.006963872	0.006939708	644.5236191	92552.48257	0.5	0.993060292	92874.74348	1325455.754	14.27143367
2022	Female	67	0.007569539	0.007540998	695.5079338	91882.46679	0.5	0.992459002	92230.22076	1232903.272	1

6 Conclusion

Brief Summary

In conclusion, the construction of mortality table experiences 4 parts of process:

- the calculation of observed death count and the exposure from the raw data (which is calculated completely in Microsoft Excel).
- Choose the best fitted model by the likelihood ratio test and AIC, BIC criteria, to model the fitted values of death count and exposure, with the calculation of fitted mortality rate followed.
- the assessment of the model, including the residual analysis, upper tail assessment, and the forecasting part.
- The final construction of the mortality table.

Although the model behaves significantly well in the view of the consistency with the observed data, the anscombe residual, simulated DHARMA residual, indicates that there may be some assumptions of the model is violated in the exposure model. Moreover, due to the lack of data, many problems are formed, including the unreasonable upper tails for the age variable and the inaccurate forecast to the further year from 2023 to 2025. Finally, we construct the mortality table for all the fitted data that is concordant with the reality. It includes 15 tables, for female, male and combined sex data, each within 5 years.

Other Results

From the mortality table, we have some small results derived:

Mortality Table Results:

- i) The mortality rate will generally decrease in the next few years, leading to a corresponding decreasing insurance fee.
- ii) The mortality rate for male is higher than that of female for most of years and of ages, leading to the higher insurance fee for male than female.

Possible Reasons for this:

- i) The mitigation of COVID19 over years
- ii) Increasing life welfare of people
- iii) Improvement of medical technology and level.
- iv) The innate mortality rate of male is higher than female naturally

Moreover, if we plot the male mortality rate and the female mortality rate, which is shown as the figure below (for those forecasting years):

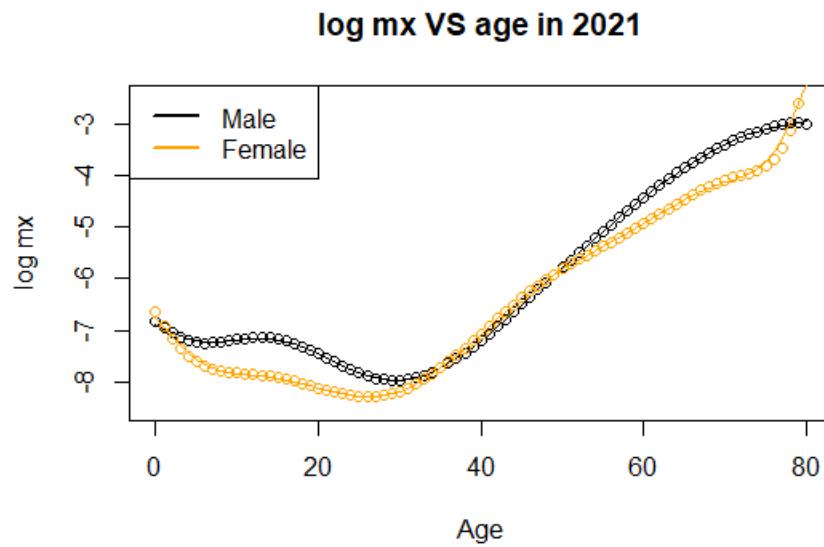


Figure 43: Male and Female Mortality Rate in 2021

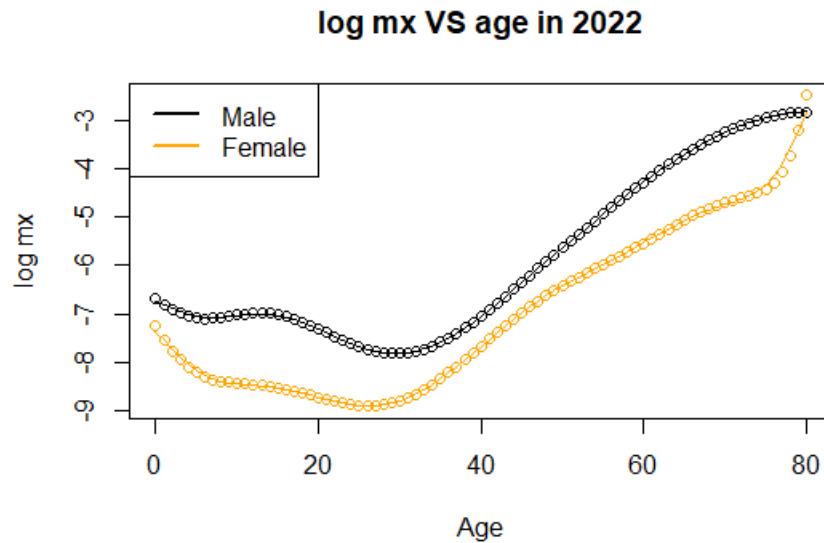


Figure 44: Male and Female Mortality Rate in 2022

The mortality rate for female is generally lower than male for the whole life span. As acknowledged, The mortality table is used for deciding the insurance policy. Thus, this will lead to a generally higher cost of insurance fee for male.

Known Advantages and Weakness

Advantages:

- i) fit the model very well in view of overdispersion, and have one age brackets for the precise prediction
- ii) Resemble the generic pattern that appears in most of the life table over the world very precisely

- iii) Can predict the further two-year mortality rate with minor fluctuations

Deficiencies:

- i) The residuals of the exposure model behave not precisely well
- ii) Cannot predict the upper tail mortality
- iii) Huge discrepancies with reality for the further year predictions after 2023

With more data, (e.g., the observed death count and the exposure for the age span from 80's to 100's, the observed data for more years for us to forecast for further years, or even census for the Ghana demographic), the upper tail problem and the forecasting sensitivity to the year can be efficaciously solved, though the exposure data may not fit the prerequisites of the Negative Binomial Model [3]. The residual problem might not be possible to be mitigated, many other models and methods are also provided for the demographical models, such as Lee-Carter Models. These methods can be applied simultaneously to compare which is the best model for the Ghana mortality rate and the construction of mortality table.

7 Acknowledgments

We are deeply indebted to the Department of Mathematical Science in University of Liverpool, most especially to all the affable lecturers, including but not limited to Dr. Ian Thompson, Dr. Kai Liu and Dr. Alena Haddley, who taught us useful preliminary knowledge for modelling and analysing data.

We are also strongly grateful to the MATH391 Summer Industrial Project Team for giving us the first foray into the experience of processing formal academic projects. We would like to extend our gratitude to the module leader Dr. Corina Constantinescu, who organizes this extraordinary activity every year successfully, and Dr. Rock Zhu, who came to Liverpool from Dutch and gave us incessant help and guidance during the summer.

Finally, We would like to express our sincere appreciation to our Tutor, Mr. Cedric Koffi and our supervisor Dr. Emmanuel Coffie, who were involved during the whole summer session, and gave us significant support consistently. Without their help, we would not accomplish such exacting and onerous works by ourselves.

A Appendix: R code

Provided below are R codes used for the entire thesis.

Note: Since the R codes are significantly repetitious for Female, Male and Total models, we choose the R codes for female model here for example.

```
#Import data
#Importing data: Female
FemaleMortality <- read.table("FemaleMortality.csv", header = TRUE, sep=",")
FemaleMortality <- FemaleMortality[, -c(1)]
FemaleMortality <- na.omit(FemaleMortality)
attach(FemaleMortality)

#Modeling
dx <- FemaleMortality$dx
Age <- FemaleMortality$Age
Year <- FemaleMortality$Year
Exposure <- FemaleMortality$Exposure
library(MASS)
#Section 2

#Section 2.2
#3D plot of the observed death count data
library(rgl)
plot <- plot3d(Age, Year, dx,
xlab = "Age", ylab = "Year", zlab = "death count", type = "s", size = c(1),
col = c('blue', 'orange', 'yellow'), ylim = c(2018,2020))

library(htmlwidgets)
rglwidget(x = scene3d(plot), width = figWidth(), height = figHeight(),
webGLoptions = list(preserveDrawingBuffer = TRUE),
shinyBrush = NULL, )

#Section 2.3
#3D plot of the observed exposure data
library(rgl)
plot <- plot3d(Age, Year, Exposure,
xlab = "Age", ylab = "Year", zlab = "death count", type = "s", size = c(1),
col = c('blue', 'orange', 'yellow'), ylim = c(2018,2020))

library(htmlwidgets)
rglwidget(x = scene3d(plot), width = figWidth(), height = figHeight(),
webGLoptions = list(preserveDrawingBuffer = TRUE), shinyBrush = NULL, )

#Section 2.4
#3D plot of the observe mortality rate
library(rgl)
plot <- plot3d(Age, Year, log(Observedmx+0.01),
xlab = "Age", ylab = "Year", zlab = "Observed Mortality Rate", type = "s", size = c(1),
col = c('blue', 'orange', 'yellow'), ylim = c(2018,2020))

library(htmlwidgets)
rglwidget(x = scene3d(plot), width = figWidth(), height = figHeight(),
webGLoptions = list(preserveDrawingBuffer = TRUE), shinyBrush = NULL, )
```

```

#Section 3

#Section 3.1.2
#Display of some examples for Negative Binomial Distribution
library(dplyr)
library(ggplot2)

#NB(5,.25)
data.frame(x = 0:30, prob = dnbinom(x = 0:30, size = 4,prob = 4/9)) %>%
  mutate(Failures = ifelse(x == 4, 4, "other")) %>%
  ggplot(aes(x = factor(x), y = prob, fill = Failures)) +
  geom_col() +
  geom_text(
    aes(label = round(prob,2), y = prob + 0.01),
    position = position_dodge(0.9),
    size = 3,
    vjust = 0
  ) +
  labs(title = "Histogram for y ~ NB(mu = 5, kappa = 0.25)",
       subtitle = "The example of y=4 is marked red",
       x = "Failed Trials y", y = "Probability")

#NB(5,1)
data.frame(x = 0:30, prob = dnbinom(x = 0:30, size = 1, prob = 1/6)) %>%
  mutate(Failures = ifelse(x == 4, 4, "other")) %>%
  ggplot(aes(x = factor(x), y = prob, fill = Failures)) +
  geom_col() +
  geom_text(
    aes(label = round(prob,2), y = prob + 0.01),
    position = position_dodge(0.9),
    size = 3,
    vjust = 0
  ) +
  labs(title = "Histogram for y ~ NB(mu = 5, kappa = 1)",
       subtitle = "The example of y=4 is marked red",
       x = "Failed Trials y",
       y = "Probability")

#NB(10,.25)
data.frame(x = 0:30, prob = dnbinom(x = 0:30, size = 4, prob = 4/14)) %>%
  mutate(Failures = ifelse(x == 4, 4, "other")) %>%
  ggplot(aes(x = factor(x), y = prob, fill = Failures)) +
  geom_col() +
  geom_text(
    aes(label = round(prob,2), y = prob + 0.01),
    position = position_dodge(0.9),
    size = 3,
    vjust = 0
  ) +
  labs(title = "Histogram for y ~ NB(mu = 10, kappa = 0.25)",
       subtitle = "The example of y=4 is marked red",
       x = "Failed Trials y",
       y = "Probability")

```

```

#NB(10,1)
data.frame(x = 0:30, prob = dnbinom(x = 0:30, size = 1, prob = 1/11)) %>%
  mutate(Failures = ifelse(x == 4, 4, "other")) %>%
  ggplot(aes(x = factor(x), y = prob, fill = Failures)) +
  geom_col() +
  geom_text(
    aes(label = round(prob,2), y = prob + 0.01),
    position = position_dodge(0.9),
    size = 3,
    vjust = 0
  ) +
  labs(title = "Histogram for y ~ NB(mu = 10, kappa = 1)",
       subtitle = "The example of y=4 is marked red",
       x = "Failed Trials y",
       y = "Probability")

#Section 3.2 Construction of Model
#Poisson Regression Model test the over-dispersion
fit <- glm(dx~poly(Year,2)+poly(Age,3),offset(log(ex)),
           data=FemaleData, family=poisson())
c<-deviance(fit)/df.residual(fit)
c

#Section 3.2.2 Likelihood Ratio Test
#Likelihood Ratio Test
#Case 1
model.1<-glm.nb(dx~log(ex)+poly(Year,1)+poly(age,4),
                  data=MaleData,link=log)
model.2<-glm.nb(dx~log(ex)+poly(Year,2)+poly(age,4),
                  data=MaleData,link=log)
library(lmtest)
lrtest(model.1,model.2)

#Case 2
model.3<-glm.nb(ex~poly(Year,1)+poly(age,9),
                  data=MaleData,link=log)
model.4<-glm.nb(ex~poly(Year,1)+poly(age,10),
                  data=MaleData,link=log)
library(lmtest)
lrtest(model.3,model.4)

#Section 3.2.3
#AIC
model.5<-glm.nb(dx~poly(Year,2)+poly(age,3)+offset(log(ex))
                  ,data=FemaleData,link=log)
model.6<-glm.nb(dx~poly(Year,2)+poly(age,3)+log(ex)
                  ,data=FemaleData,link=log)
summary(model.5,correlation=F)
summary(model.6,correlation=F)

#BIC
BIC(model.5)
BIC(model.6)

```

```

#Section 3.2.4 Modeling of Death Count
#take 2018 as the example
model.6<-glm.nb(dx~poly(Year,2)+poly(age,3)+log(ex),
                  ,data=Femaledata,link=log)
x <- seq(0, 77)
d<- dx[1:78]
fit2018 <- fitted.values(model.6)[0:78]
plot(x, d,type = "n", xlab="age",ylab = "dx",
      main="death count and its fit in 2018")
lines(smooth.spline(x,d,df = 15))
par(new=TRUE)
points(x, fit2018,col = "red", type = "n", ylab = NULL)
lines(smooth.spline(x,fit2018,df = 15),col = "red")

#Section 3.2.5 Modeling of Exposure
#take 2018 as the example
model.7<-glm.nb(ex~poly(Year,1)+poly(age,10),
                  ,data=Femaledata,link=log)
x <- seq(0, 77)
e<- ex[1:78]
fit2018 <- fitted.values(model.7)[1:78]
plot(x, e,ylim=c(0, 4000),type = "n", xlab="age",ylab = "exposure",
      main="exposure and its fit in 2018")
lines(smooth.spline(x,e,df = 15))
par(new=TRUE)
points(x, fit2018,col = "red", type = "n", ylab = NULL)
lines(smooth.spline(x,fit2018,df = 15),col = "red")

#Section 3.3
#Derivation and plots of the fitted mortality rate
Observedmx <- dx / Exposure #Observed death rate

a0 <- predict.glm(model.ex10, newdata = data.frame(Age = 0:80, Year = 2018),
                   ,type = "response")
b0 <- predict.glm(model.7, newdata = data.frame(Age = 0:80, Year = 2018,
                                                 Exposure = a0), type = "response")
Modeledmx2018 <- b0 / a0      #2018

a1 <- predict.glm(model.ex10, newdata = data.frame(Age = 0:80, Year = 2019),
                   ,type = "response")
b1 <- predict.glm(model.7, newdata = data.frame(Age = 0:80, Year = 2019,
                                                 Exposure = a1), type = "response")
Modeledmx2019 <- b1 / a1    #2019

a2 <- predict.glm(model.ex10, newdata = data.frame(Age = 0:80, Year = 2020),
                   ,type = "response")
b2 <- predict.glm(model.7, newdata = data.frame(Age = 0:80, Year = 2020,
                                                 Exposure = a2), type = "response")
Modeledmx2020 <- b2 / a2    #2020
x <- seq(0, 80)
y <- seq(0, 77)
plot(x, log(Modeledmx2019+0.001),xlab = "Age", ylab = "log mx",
      main ="log mx and its fitted values in 2019", ylim = c(-7.5, -3))
lines(smooth.spline(y,log(Observedmx[79:156]+0.001),df = 15), col = "blue")

```

```

par(new=TRUE)
points(y, log(Observedmx[79:156]+0.001), col = "blue", ylab = NULL)
lines(smooth.spline(x, log(Modeledmx2019+0.001), df = 15))

x <- seq(0, 80)
y <- seq(0, 77)
plot(x, log(Modeledmx2020+0.001), xlab = "Age", ylab = "log mx", main =
"log mx and its fitted values in 2020", ylim = c(-7.5, -3))
lines(smooth.spline(y, log(Observedmx[157:234]+0.001), df = 15), col = "blue")
par(new=TRUE)
points(y, log(Observedmx[157:234]+0.001), col = "blue", ylab = NULL)
lines(smooth.spline(x, log(Modeledmx2020+0.001), df = 15), col = "black")

x <- seq(0, 80)
y <- seq(0, 77)
plot(x, log(Modeledmx2018+0.0001), xlab = "Age", ylab = "log
mx and its fitted value in 2018")
lines(smooth.spline(y, Observedmx[1:78]+0.0001, df = 15), col = "blue")
par(new=TRUE)
points(y, Observedmx[1:78]+0.0001, col = "blue", ylab = NULL)
lines(smooth.spline(x, Modeledmx2018+0.0001, df = 15), col = "black")

#Section 4.1 Residual Analysis
#Section 4.1.1 Deviance Residual

#Deviance Residual Plot for dx model
devres <- residuals.glm(model.7, type = "deviance")
plot(fitted.values(model.7), devres, xlab = "Fitted Values
of Death Count",
      ylab = "Deviance Residual", main = "Deviance Residual Plot
for Female
Death Count Model")
abline(h = seq(-2.5, 3.2, by = 0.4), v = -1:18, col =
"lightgray", lty = 3)
lines(smooth.spline(fitted.values(model.7), devres, df = 10
), col = "red")
lines(smooth.spline(fitted.values(model.7), devres, df = 25
), col = "blue")
lines(smooth.spline(fitted.values(model.7), devres, df = 40
), col = "green")
legend("topright",
      legend=c("10-degree spline", "25-degree spline", "40
-degree spline"),
      col=c("red", "blue", "green"),
      lty=1, lwd=2)

#Deviance Residual Plot for Exposure Model
devres <- residuals.glm(model.ex10, type = "deviance")
plot(fitted.values(model.ex10), devres, xlab = "Fitted Val
ues of Exposure",
      ylab = "Deviance Residual", main = "Deviance Residual
Plot for Female"

```

```

    Exposure Model")
abline(h = seq(-6.9, 3.2, by = 0.4), v = seq(0, 4500, by = 200
), col = "lightgray", lty = 3)
lines(smooth.spline(fitted.values(model.ex10), devres, df = 10
), col = "red")
lines(smooth.spline(fitted.values(model.ex10), devres, df = 25
), col = "blue")
lines(smooth.spline(fitted.values(model.ex10), devres, df = 40
), col = "green")
legend("bottomright",
       legend=c("10-degree spline", "25-degree spline", "40-
degree spline"),
       col=c("red", "blue", "green"),
       lty=1, lwd=2)

#Section 4.1.2 Anscombe Residual
library(surveilance)
ansresdx <- anscombe.residuals(m = model.7, phi = 1)
hist(ansresdx, breaks = 10, col = "purple", xlab =
"Anscombe Residual", main = "Histogram of Anscombe
Residuals of Female dx Model")
qqnorm(ansresdx, col = "orange", main = "Normal Q-Q Plot
for Death Count")
qqline(ansresdx, col = "blue")
ansresex <- anscombe.residuals(m = model.ex10, phi = 1)
hist(ansresdx, breaks = 10, col = "purple", xlab =
"Anscombe Residual", main = "Histogram of Anscombe
Residuals of Female Exposure Model")
qqnorm(ansresex, col = "orange", main = "Normal Q-Q Plot
for Exposure")
qqline(ansresex, col = "blue")

library(nortest)
ad.test(ansresdx)
ad.test(ansresex)

#Section 4.1.3 Simulated Residual: DHARMA Package
library(DHARMA)
simulationOutput <- simulateResiduals(model.7, plot = T)
simulationOutputex <- simulateResiduals(model.ex10, plot = T)
testDispersion(simulationOutput)
testDispersion(simulationOutputex)

#Section 4.3
#Forecasting and the 3D plot
a3 <- predict.glm(model.ex10, newdata = data.frame(Age = 0:80, Year = 2021)
                  , type = "response")
b3 <- predict.glm(model.7, newdata = data.frame(Age = 0:80, Year = 2021,
                                                 Exposure = a3), type = "response")
Modeledmx2021 <- b3 / a3 #2021

a4 <- predict.glm(model.ex10, newdata = data.frame(Age = 0:80, Year = 2022)
                  , type = "response")
b4 <- predict.glm(model.7, newdata = data.frame(Age = 0:80, Year = 2022,

```

```

Exposure = a4), type = "response")
Modeledmx2022 <- b4 / a4 #2022

a5 <- predict.glm(model.ex10, newdata = data.frame(Age = 0:80, Year = 2023)
                   ,type = "response")
b5 <- predict.glm(model.7, newdata = data.frame(Age = 0:80, Year = 2023,
                                                 Exposure = a5), type = "response")
Modeledmx2023 <- b5 / a5 #2023

a6 <- predict.glm(model.ex10, newdata = data.frame(Age = 0:80, Year = 2024)
                   ,type = "response")
b6 <- predict.glm(model.7, newdata = data.frame(Age = 0:80, Year = 2024,
                                                 Exposure = a6), type = "response")
Modeledmx2024 <- b6 / a6 #2024

a7 <- predict.glm(model.ex10, newdata = data.frame(Age = 0:80, Year = 2025)
                   ,type = "response")
b7 <- predict.glm(model.7, newdata = data.frame(Age = 0:80, Year = 2025,
                                                 Exposure = a7), type = "response")
Modeledmx2025 <- b7 / a7 #2025

library(rgl)
plot <- plot3d(Age, Year, log(mx),
xlab = "Age", ylab = "Year", zlab = "log mortality rate", type = "s", size = c(0.5),
col = c('blue', 'orange', 'yellow'), ylim = c(2018,2025), zlim = c(-11, -3))

#Section 5.2
#Construction of life table
#Year for dataframe
Year <- c[1:405]
Year[1:81] <- c(2018)
Year[82:162] <- c(2019)
Year[163:243] <- c(2020)
Year[244:324] <- c(2021)
Year[325:405] <- c(2022)

#Age for dataframe
Age <- c[1:405]
Age[1:81] <- seq(0, 80)
Age[82:162] <- seq(0, 80)
Age[163:243] <- seq(0, 80)
Age[244:324] <- seq(0, 80)
Age[325:405] <- seq(0, 80)
#mx for dataframe
mx <- c[1:405]
mx[1:81] <- Modeledmx2018
mx[82:162] <- Modeledmx2019
mx[163:243] <- Modeledmx2020
mx[244:324] <- Modeledmx2021
mx[325:405] <- Modeledmx2022

#ax for dataframe
ax <- c[1:405]
mx[1]

```

```

mx[82]
mx[163]
mx[244]
mx[325]
ax[1] <- 0.14903 - 2.05527 * mx[1]
ax[82] <- 0.14903 - 2.05527 * mx[82]
ax[163] <- 0.14903 - 2.05527 * mx[163]
ax[244] <- 0.14903 - 2.05527 * mx[244]
ax[325] <- 0.14903 - 2.05527 * mx[325]
ax[2:81] <- c(0.5)
ax[83:162] <- c(0.5)
ax[164:243] <- c(0.5)
ax[245:324] <- c(0.5)
ax[326:405] <- c(0.5)
#qx for dataframe
qx <- c[1:405]
qx <- mx / (1 + (1 - ax) * mx)
#px for dataframe
px <- c[1:405]
px <- (1 - qx)
#lx for dataframe
lx <- c[1:405]
lx[1] <- 100000
lx[82] <- 100000
lx[163] <- 100000
lx[244] <- 100000
lx[325] <- 100000

i <- 2
while (i <= 81) {
  lx[i] = lx[i-1] * px[i-1]
  i = i + 1
}

i <- 83
while (i <= 162) {
  lx[i] = lx[i-1] * px[i-1]
  i = i + 1
}

i <- 164
while (i <= 243) {
  lx[i] = lx[i-1] * px[i-1]
  i = i + 1
}

i <- 245
while (i <= 324) {
  lx[i] = lx[i-1] * px[i-1]
  i = i + 1
}

i <- 326
while (i <= 405) {

```

```

lx[i] = lx[i-1] * px[i-1]
i = i + 1
}
#dx for dataframe
dx <- c[1:405]
dx <- lx * qx
#Lx for dataframe
Lx <- c[1:405]
Lx <- lx - (1 - ax) * dx
#Tx for dataframe
Tx <- c[1:405]
Tx[1:405] <- 0

i <- 81
while (i >= 1) {
  Tx[i] = Tx[i+1] + Lx[i]
  i = i - 1
}

i <- 162
while (i >= 82) {
  Tx[i] = Tx[i+1] + Lx[i]
  i = i - 1
}

i <- 243
while (i >= 163) {
  Tx[i] = Tx[i+1] + Lx[i]
  i = i - 1
}

i <- 324
while (i >= 244) {
  Tx[i] = Tx[i+1] + Lx[i]
  i = i - 1
}

Tx[405] = Lx[405]
i <- 404
while (i >= 325) {
  Tx[i] = Tx[i+1] + Lx[i]
  i = i - 1
}
Tx[1:81] <- Tx[1:81] + lx[81] * px[81] * ax[81]
Tx[82:162] <- Tx[82:162] + lx[162] * px[162] * ax[162]
Tx[163:243] <- Tx[163:243] + lx[243] * px[243] * ax[243]
Tx[244:324] <- Tx[244:324] + lx[324] * px[324] * ax[324]
Tx[325:405] <- Tx[325:405] + lx[405] * px[405] * ax[405]

#ex for dataframe
ex <- c[1:405]
ex = Tx / lx

MortalityTableFemale <- data.frame(Year, Age, mx, qx, ax, px, lx, dx, Lx, Tx, ex)

```

References

- [1] David B Atkinson and John K McGarry. “Experience Study Calculations”. In: *United States: Society of Actuaries* 73 (2016).
- [2] H. Booth and L. Tickle. “Mortality Modelling and Forecasting: a Review of Methods”. In: *Annals of Actuarial Science* 3.1-2 (2008), pp. 3–43. DOI: 10.1017/S1748499500000440.
- [3] Emmanuel Coffie. “A comparison of Poisson or Negative Binomial Regression and Lee-Carter Models of forecasting Norwegian male mortality”. MA thesis. 2015.
- [4] Piet De Jong, Gillian Z Heller, et al. “Generalized linear models for insurance data”. In: *Cambridge Books* (2008).
- [5] Antoine Delwarde, Michel Denuit, and Christian Partrat. “Negative binomial version of the Lee–Carter model for mortality forecasting”. In: *Applied Stochastic Models in Business and Industry* 23.5 (2007), pp. 385–401. DOI: <https://doi.org/10.1002/asmb.679>. eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/asmb.679>. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1002/asmb.679>.
- [6] Cindy Feng, Longhai Li, and Alireza Sadeghpour. “A comparison of residual diagnosis tools for diagnosing regression models for count data”. In: *BMC Medical Research Methodology* 20.1 (2020), pp. 1–21.
- [7] Finnstats. *Likelihood Ratio Test in R with Example*. <https://finnstats.com/index.php/2021/11/24/likelihood-ratio-test-in-r/>. Accessed August 10, 2022. 2020.
- [8] Florian Hartig. *DHARMA: Residual Diagnostics for Hierarchical (Multi-Level / Mixed) Regression Models*. R package version 0.4.6. 2022. URL: <http://florianhartig.github.io/DHARMA/>.
- [9] Diane Lambert. “Zero-inflated Poisson regression, with an application to defects in manufacturing”. In: *Technometrics* 34.1 (1992), pp. 1–14.
- [10] Jerald F. Lawless. “Negative binomial and mixed Poisson regression”. In: *Canadian Journal of Statistics* 15.3 (1987), pp. 209–225. DOI: <https://doi.org/10.2307/3314912>. eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.2307/3314912>. URL: <https://onlinelibrary.wiley.com/doi/abs/10.2307/3314912>.
- [11] Peter McCullagh and John A Nelder. *Generalized linear models*. Routledge, 2019.
- [12] Shanaaz Rademeyer. “Provincial differentials in under-five mortality in South Africa.” PhD thesis. 2017.
- [13] John R Wilmoth et al. “Methods protocol for the human mortality database”. In: *University of California, Berkeley, and Max Planck Institute for Demographic Research, Rostock*. URL: <http://mortality.org> [version 31/05/2007] 9 (2007), pp. 10–11.
- [14] Zach. *How to Interpret Null and Residual Deviance (With Examples)*. <https://www.statology.org/null-residual-deviance/>. Accessed August 10, 2022. 2020.
- [15] Michael L Zwilling. “Negative binomial regression”. In: *The Mathematica Journal* 15 (2013), pp. 1–18.