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Ahmed Tamimu
Department of Statistics and Actuarial Science, School of Mathematical Sciences, C. K. Tedam University of Technology and Applied Sciences, Navrongo, Ghana.

Suleman Nasiru
Department of Statistics and Actuarial Science, School of Mathematical Sciences, C. K. Tedam University of Technology and Applied Sciences, Navrongo, Ghana.

Dioggban Jakperik
Department of Biometry, School of Mathematical Sciences, C. K. Tedam University of Technology and Applied Sciences, Navrongo, Ghana.

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The authors declare that there is no conflict of interest.

Data Availability

The data for the study is available upon reasonable request from the corresponding author.

Author Contributions

TA derived methods, performed simulation studies and wrote the initial draft of the article. NS conceptualized the research and led the simulation. JD wrote the methodology and proofread the article.

ORIGINAL STUDY

Cure Rate Analysis of National Health Insurance Scheme Claims Payment Survival Times in Ghana: The Case of Pru District

Ahmed Tamimu [a,*], Suleman Nasiru [a], Dioggban Jakperik [b]

[a] Department of Statistics and Actuarial Science, School of Mathematical Sciences, C. K. Tedam University of Technology and Applied Sciences, Navrongo, Ghana
[b] Department of Biometry, School of Mathematical Sciences, C. K. Tedam University of Technology and Applied Sciences, Navrongo, Ghana

Abstract

In this study, cure models have been applied to model National Health Insurance Scheme (NHIS) claims payment data with cured proportion using Pru District in the Bono East Region of Ghana as a case study. The covariates effects were also modelled to investigate the effects of the covariates on the cured proportion. The estimates of the parameters of the models were obtained by directly maximizing the observed likelihood functions. Most estimates of the parameters of the cure models are significant at 5% significance level. The study revealed that the cured claims payments rate increases over time with an estimated cured rate of 23.2%. Most covariates are significant at 5% significance level in most of the cure regression models, thus, the covariates, number of NHIA staff vetting the claims and claims submission category contribute to the claims payments cure rate. Weibull cure model modelled the data best over the competitive models. To ensure the sustainability of the scheme and the attainment of Universal Health Coverage (UHC) by 2030 in Ghana, the health policy makers should prioritise claims payments to Healthcare Providers (HCPs) at the primary health care (PHC) levels within time over HCPs above PHC level.

Keywords: Cure rate models, National Health Insurance Scheme, Claims payment survival times, Pru District, Ghana

1. Introduction

Modelling the time it takes for a specific event of interest to occur has gained the attention of researchers in many scientific studies in recent times. In modelling such data, it is common for subsets of the study population to never experience the event of interest. These subsets of the population are considered as the cured population and are also immune to the event of interest occurring within the study period [28]. In application, survival times with cured proportions are available in National Health Insurance Scheme (NHIS) claims payments as some claims payments were never made within the legally 90 days period as established by ACT 852 [22] of the NHIS. These claims payments are considered as cured claims and are immune to the payment occurring within the specified time frame since it was paid after the 90 days period. Hence cure models should be used for modelling such claims data. Cure models are survival models that consider the possibility of cured subjects [28]. These models are classified into mixture and non-mixture models depending on how the cured fraction is introduced into the model. There are several mixture cure models that have been applied to model survival data with cured fraction including [1,6,17,20,24,26]. Another class of cure model for modelling cured proportion of survival data is the non-mixture cure model. Some applications of non-mixture cure models on cured data are [1,5,6,8,14,17,29,30].

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* Corresponding author.
E-mail address: ahmedtamimu@yahoo.com (A. Tamimu).

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Moreover, defaults in claims refund to healthcare providers (HCPs) have been a pitfall to the survival of the scheme and the attainment of Universal Health Coverage (UHC) in Ghana by the year 2030. Some of the researches on the NHIS include [2,3,4,7,8,15].

Despite the significant progress made on the application of cure models on cured fraction data in recent years, which are limited to some areas of applications [27,31] and the significant research works on NHIS, there is no work that has been done on the empirical application of cure models on NHIS claims payment survival times in Ghana. Therefore, in this study, cure rate models have been applied to model NHIS claims payment survival times in Ghana.

The rest of the article is structured as follows: Section 2 presents the methodology applied to obtain the results; application of the cure models and the cure regression models on the claims payment survival times, discussions of results are presented in Section 3 and conclusion of the research is presented in Sections 4.

2. Methodology

2.1. Study area

The study was carried out in the Pru District of Bono East Region. Pru District is one of 163 administrative District offices of the National Health Insurance Authority (NHIA) backed by law following the passage of the National Health Insurance ACT, 2003, [21]. This is one of the decentralized district offices of the NHIA which ensures the implementation of NHIS as a social Health Insurance Scheme in the District. The District office among other responsibilities is to ensure the general operations of the scheme including management of claims received from the HCPs in the District. The Pru District is in between longitudes $0^0 30''$W and $1^0 26''$W and latitudes $7^0 50''$N and $8^0 22''$N. It is bounded by six (6) other Districts in the Bono East Region which are Nkoranza and Atebubu-Amantin to the South, Kintampo North and Kintampo South to the West, Sene East and Sene West to the East and East Gonja District in the Savannah Region to the North. The Pru District has a total land area of 3220.7 km square [11]. The District has a total population of 170,928 inhabitants [12] with the major economic activities of the people being farming and fishing [11]. Moreover, it is worthy to note that, the Pru District was selected for the study because the HCPs in the District are all at the primary healthcare (PHC) level. These included the District hospital owned by the Christian Health Association of Ghana (CHAG), health centres/clinics and Community-based Health Planning and Services (CHPS) compounds which remain central in attaining Universal Health Coverage (UHC) in Ghana by 2030. The CHPS is a national policy which aims at providing essential community based health services to every demarcated geographical area which may be the same as electoral areas [18]. However, the District has 19 functional CHPS compounds representing 50% of CHPS compound coverage out of 38 CHPS Zones [10] since the introduction of the CHPS compound. Thus, delays in NHIS claims payment to these facilities hinder continuous access to health care delivery in the district under NHIS as these CHPS compounds are challenged in terms of the availability of basic infrastructure and equipment to operate [18]. The map of the District is shown in Fig. 1.

2.2. Data and sources

The study used Ghana's NHIS monthly claims payment survival times obtained from the NHIA, Pru District Office. The claims payment survival times was calculated from the date of submission of claims to the date of claims payment. These payments were made under the Ghana-diagnoses related grouping (G-DRG) and fee-for medicines payment methods. These payments covered Outpatient (OPD) and In-patient (IPD) primary healthcare services and medicines accessed by the active card bearing members of the scheme. Other factors that influence the claims payments include length of vetting of claims, number of NHIA staff vetting the claims at the District level and category of claims submission (Timely submission = 0, late submission = 1) are considered in the data set.

2.3. Mixture cure rate models

Mixture cure rate models classified the population into two groups, which are the cured and uncured subpopulations. Thus, the mixture cure model is given as;

$$S(t) = pS_u(t) + (1-p), \tag{1}$$

where p is defined as the probability of the claims payment survival times being cured and $S_u(t)$ is the

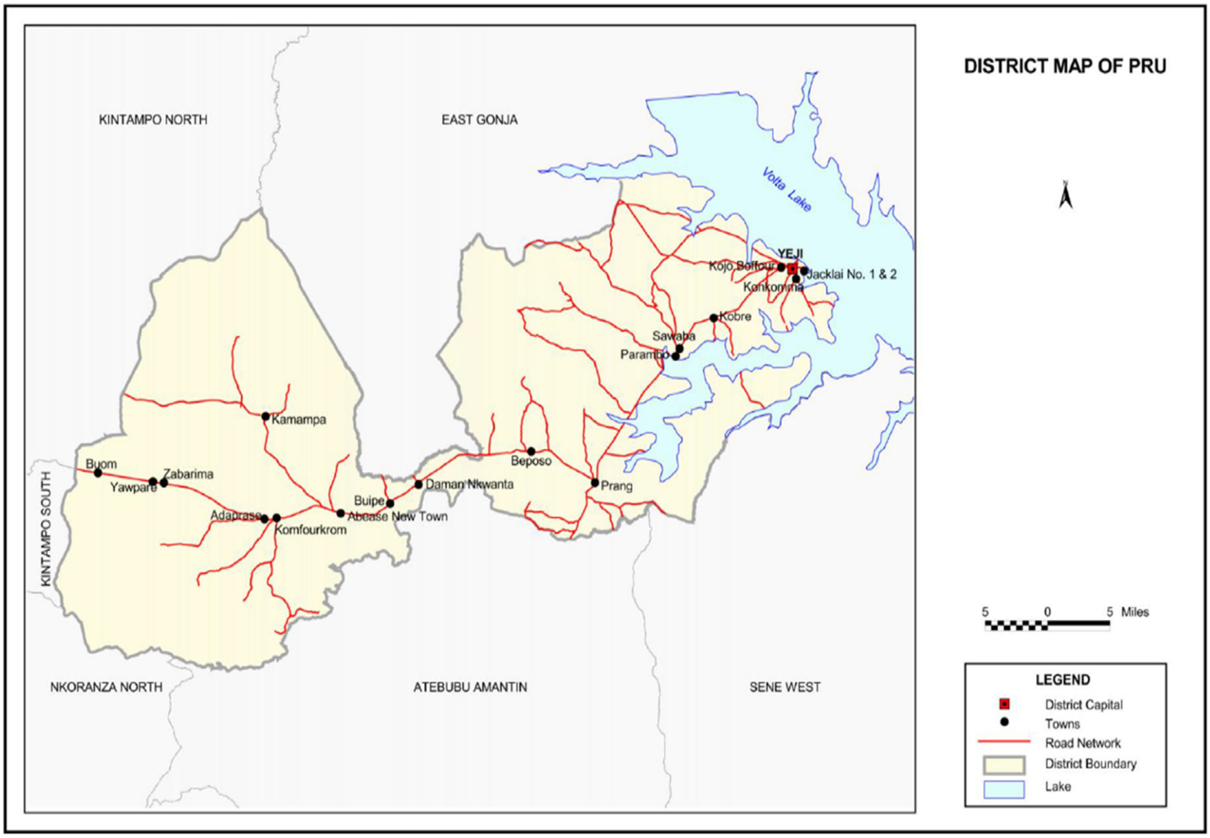

Fig. 1. Map of Pru District (Ghana statistical service, 2010).

survival function (SF) for uncured (u) claims payment [28].

2.4. Non-mixture cure rate models

Any batch of claims submitted to the NHIA for payment has some number of days it takes for the claims payment to occur. Assume that this batch of claims follows a Poisson distribution, then the claims payment which were made within the regulated time frame is defined by a random variable T such that

$$T = \min\{\overline{T}_1, ..., \overline{T}_N\} = \overline{T}_{(1)}, \tag{2}$$

where $\overline{T}_i{}'s$ are independently identically distributed with underlying CDF and SF, $F(.)$ and $S(.)$ respectively [16]. Thus the SF of the random variable T is given as;

$$\begin{aligned} S(t) &= P(N=0) + P(\overline{T}_1 > t, ..., \overline{T}_N > t, N \geq 1) \\ &= \mathrm{e}^{-\lambda} + \sum_{k=1}^{\infty} \frac{\left[S^H(t)\lambda\right]^k}{k!} e^{-\lambda} \\ &= e^{-\lambda + S(t)} \\ &= e^{-\lambda G(t)} \\ &= P^{G(t)}, \end{aligned} \tag{3}$$

where $p = e^{-\lambda} > 0$ is the cure probability [28].

2.5. Survival distribution models

The survival distribution models employed to model the claims payment survival times include Weibull, exponential, gamma, log-logistic and log-normal survival models using both the mixture and non-mixture cure model structure. The survival models are;

$$\begin{aligned}
&\text{Weibull survival function}: S(t)=e^{-\left(\frac{t}{\sigma}\right)^{\zeta}}, && t>0,\\
&\text{Exponential survival function}: S(t)=e^{-\frac{t}{\sigma}}, && t>0,\\
&\text{Gamma survival function}: S(t)=\int_t^{\infty}\frac{\sigma\left(\frac{t}{\sigma}\right)^{\zeta-1}e^{-\frac{t}{\sigma}}}{\Gamma(\zeta)}dt, && t>0,\\
&\text{Log}-\text{logistic survival function}: S(t)=\frac{1}{1+(\sigma t)^{\zeta}}, && t>0,\\
&\text{Lognormal survival function}: S(t)=1-\phi\left(\frac{\ln(t)-u}{\sigma}\right), && t>0,
\end{aligned} \tag{4}$$

where the scale and the shape parameters are σ and ζ respectively and $\sigma>0$ and $\zeta>0$, $\phi(z)=(1/\sqrt{2\pi})\exp(-z^2/2)$ is the PDF of the normal distribution with mean 0 and variance 1 [9,13].

2.6. Regression models

Logit link function which is the most popular method of modelling the effect of covariates on the cured proportion was used to link the cure rate p to the covariates. This is given as;

$$P_i=\frac{e^{Z_i^T\beta}}{1+e^{Z_i^T\beta}},\ i=1,2,...,n, \tag{5}$$

where $Z_i^T=(1,z_{i1},z_{i2},...,z_{ik})$ represents the i^{th} vector of covariates [1]. Where, z_{i1},z_{i2} and z_{i3} denote the claims length of vetting, NHIA vetting staff strength and claims submission category respectively, $\beta=(\beta_0,\beta_1,\beta_2,...,\beta_k)$ represents the vector coefficients of the regression model corresponding to the covariates respectively. This provides the regression model is given as;

$$\log\left(\frac{p_i}{1-p_i}\right)=\mathbf{Z}_i^T\beta,\ i=1,2,...,n. \tag{6}$$

2.7. Model estimation

Suppose that the observed data of T and its censoring indicator δ for n subjects are represented by $(t_i,\delta_i), i=1,...,n,$ where $\delta_i=1$ given t_i is not censored and $\delta_i=0$ given t_i is censored. Let $\boldsymbol{\alpha}$ be a vector of unknown parameters in the parametric baseline SF, $s_u(t)$ [28]. The log-likelihood functions of the non-mixture and mixture cure rate models are respectively given as;

$$\ell(\boldsymbol{\alpha})=\sum_{i=1}^{n}\delta_i\log f_u(t_i)+\sum_{i=1}^{n}(1-\delta_i)\log S_u(t_i)$$
and
$$\ell(\boldsymbol{\alpha})=\log\prod_{i=1}^{n}\left[pf_u(t_i)\right]^{\delta_i}\left[1-p+S_u(t_i)\right]^{1-\delta_i}, \tag{7}$$

where $f_u(t)$ and $S_u(t)$ are the PDF and the SF of the cure rate models respectively and p is the probability of being cured [28]. Thus, the Maximum likelihood estimates of the parameters of the cure rate models in equation (4) and the parameters of their associated regression models in equation (6) are obtained by direct maximization of the log-likelihood functions in equation (7).

3. Application of cure rate models

In this section, Weibull, Log-logistic, Gamma, exponential and lognormal cure rate models are fitted to the claims payment survival data, and their corresponding regression models are also fitted to the claims payment survival data to investigate the effect of covariates on the cured proportion of the claims payment survival times.

3.1. Descriptive statistics

Table 1 shows the descriptive statistics of the survival times of the claims payments. The average number of days it takes for claims payments to be made to the Healthcare Providers (HCPs) is 77.97

Table 1. Descriptive statistics of claims payments survival times.

Maximum	Minimum	Median	Mean	Skewness	Excess Kurtosis
154.00	19.00	76.50	77.97	0.9744	1.3258

days. The claims payment is positively skewed as the coefficient of skewness of 0.9744 is greater than zero. The claims payment survival data further shows a positive excess kurtosis value of 1.3258 over the normal distribution value of 3. This indicates that the distribution is leptokurtic which means it has higher and thinner peaks.

Fig. 2 shows the violin plot, boxplot and kernel density plot of the data. These plots reveal that the claims payment survival data is right skewed and also exhibit leptokurtic distribution. This confirms the results of the descriptive statistics in Table 1.

Kaplan–Meier survival curve plot which is used to show the presence of cured claims payments is obtained as shown in Fig. 3. Fig. 3 exhibits a lengthy and stable plateau that is substantially above zero levels. This indicates that some reasonable proportion of the claims payments are cured which reveals

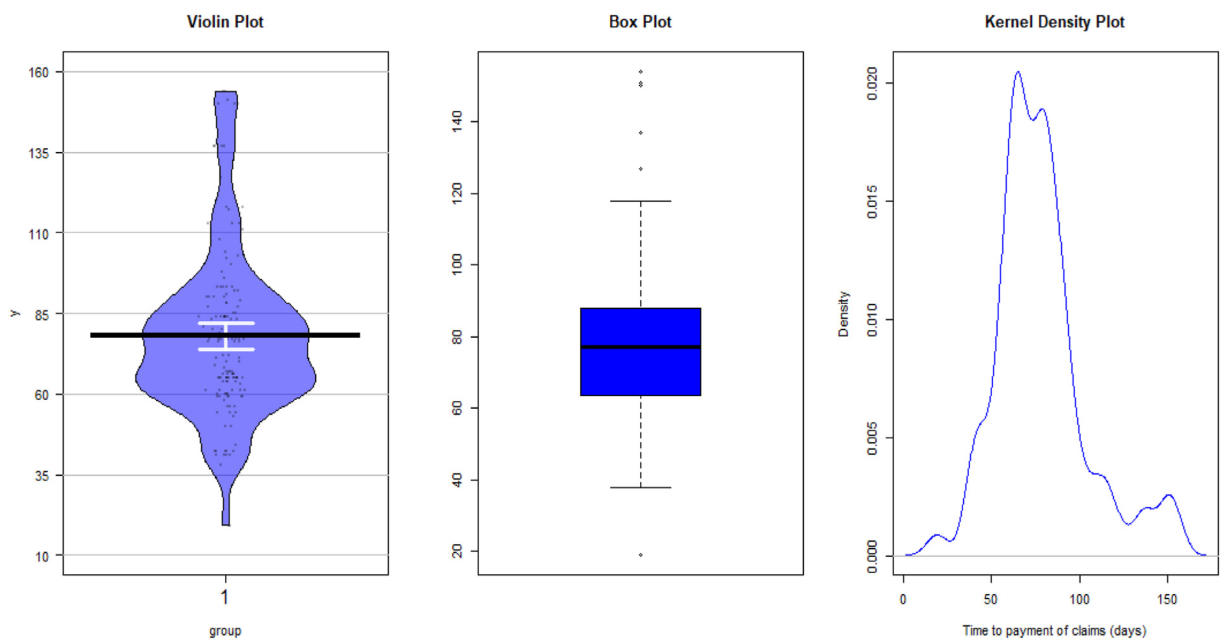

Fig. 2. Violin plot, Boxplot and Kernel Density plot.

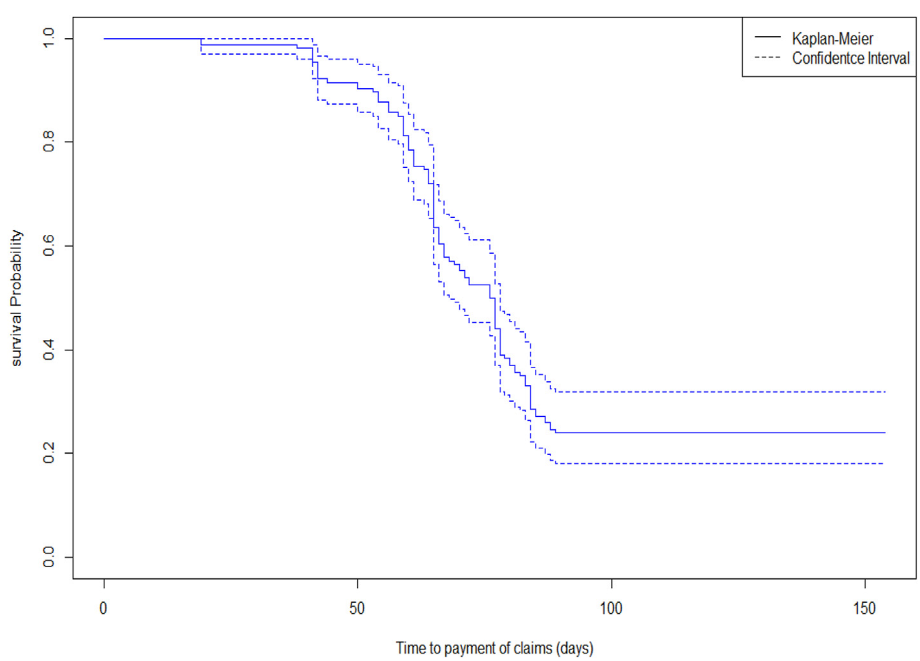

Fig. 3. Kaplan–Meier survival curve of time to claims payments.

that the claims payment survival data can be adequately modelled using cure rate models.

3.2. Cure rate models without covariates

Cure rate models are fitted to the claims payment survival data. The mixture and non-mixture cure rate models without covariates are fitted to the claims payment survival times. Table 2 shows the parameter estimates of the competitive cure rate models with their corresponding standard error and 95% confidence interval (CI) estimates. All the parameters of the cure models are significant at 5% significance level except $\hat{p}$ for the exponential cure rate models since the CI estimates of these models do not contain zero. In application, the estimated value of the shape parameter $(\hat{\zeta})$ of the cure models depicts the claims payment failure rate which measures the behaviour of the cured proportion of claims payment survival times. This reveals that the cure rate $\hat{p}$ increases over time as the shape parameter $(\hat{\zeta})$ values of all the cure models are greater than one $(\hat{\zeta} > 1)$. This further indicates that the proportion of cured claims payments increases over time whereas the uncured proprtion of the claims payments decreases over time. This is also shown in the value of the cure rate $\hat{p}$ in most of the cure rate models shown in Table 2. Thus, Weibull cure rate model estimated the cure rate of the claims payment at 23.2% whereas the uncured rate of the claims payment was estimated at 76.8%. However, the exponential cure model estimated the cure rate of claims payment at 9.05×10^{-8}% whereas the uncured claims payment was estimated at 99.99%. The result confirms the fact that the claims payments made to the PHC facilities were irregular with about 48% of the operating capital of these facilities being in debt to NHIS [19]. The results further confirm the studies by Nsiah-Boateng et al. [25] which revealed that the percentage of claims paid beyond 90 days has increased over time. This will potentially hinder financial access to PHC delivery in the District as all the healthcare facilities in the District are at the PHC levels. Therefore, these healthcare facilities would not be able to acquire the basic infrastructure, equipment, consumables and medicines among others to meet the basic healthcare needs of the residents. Thus, these healthcare facilities would resort to co-payments as well as cash and carry payment system among others which can largely affect the attainment of the UHC in Ghana by the year 2030.

The main problem to be addressed is to model the number of days it takes for claims payment to be made to the HCPs using an appropriate cure model. To achieve this, Table 3 presents the information criteria used to select the best cure model which can be used to model the claims payment survival data. The Weibull mixture and non-mixture cure rate models have the highest values of log-likelihood (ℓ), the lowest values of AIC, AICc and BIC as compared to the other competitive models. Thus, the Weibull cure rate model is the best fit model that can be used to model the claims payment survival data over the other competitive models. This is however not surprising as the data exhibits the characteristics of heavy tail distribution as seen in the positive excess kurtosis value in Table 1.

To compare the fit of the mixture cure rate models, the estimated survival curves from the mixture cure models are obtained and overlaid with the Kaplan–Meier curve as shown in Fig. 4. The Weibull

Table 2. Parameter Estimates of cure rate models without covariates.

Mixture					Non-mixture		
Model	Parameter	Estimate	Std Error	95% CI	Estimate	Std error	95% CI
	$\hat{p}$	23.2%	0.0311	(17.1%; 30.6%)[a]	23.7%	0.0316	(17.5%; 31.3%)[a]
Weibull	$\hat{\zeta}$	5.7540	0.4500	(4.9360; 6.7060)[a]	6.2980	0.4920	(5.404; 7.341)[a]
	$\hat{\sigma}$	72.541	1.2470	(70.1380; 75.0250)[a]	78.0510	1.6540	(74.876; 81.361)[a]
Log-logistic	$\hat{p}$	20.1%	0.0316	(13.9%; 28.2%)[a]	19.5%	0.0316	(13.3%; 27.6%)[a]
	$\hat{\zeta}$	7.1850	0.6320	(6.0470; 8.5370)[a]	6.9330	0.6230	(5.813; 8.268)[a]
	$\hat{\sigma}$	68.1620	1.5320	(65.2250; 71.2320)[a]	76.3920	2.3300	(71.959; 81.099)[a]
Gamma	$\hat{p}$	20.97%	0.0314	(14.81%; 28.83%)[a]	19.5%	0.0332	(13.0%; 28.2%)[a]
	$\hat{\zeta}$	15.9028	2.2506	(12.0507; 20.9863)[a]	14.2030	2.1280	(10.588; 19.052)[a]
	$\hat{\sigma}$	0.2332	0.0346	(0.1743; 0.3119)[a]	0.1800	0.0320	(0.127; 0.255)[a]
Exponential	$\hat{p}$	9.05×10^{-10}%	0.0000	(0.00; 100%)	3.96×10^{-22}%	0.0000	(6.91×10^{-55}%; 100%)
	$\hat{\sigma}$	9.74×10^{-1}	5.7810^{-3}	(3.05×10^{-03}; 3.1×10^{-02})[a]	1.98×10^{-04}	1.56×10^{4}	(4.21×10^{-5}; 9.3×10^{-4})[a]
Lognormal	$\hat{p}$	19.44%	0.0320	(13.16%; 27.75%)[a]	16.31%	0.0342	(9.61%; 26.33%)[a]
	$\hat{\zeta}$	4.2026	0.0285	(4.1468; 4.2584)[a]	4.3935	0.0553	(4.2852; 4.5019)[a]
	$\hat{\sigma}$	0.2810	0.0215	(0.2419; 0.3264)[a]	0.3210	0.0301	(0.2671; 0.3858)[a]

[a] Implies significant at 5% significance level.

Table 3. Information criteria measures of cure rate models.

	Mixture				Non-mixture			
Model	ℓ	AIC	AICc	BIC	ℓ	AIC	AICc	BIC
Weibull	**−563.9630**	**1133.9260**	**1133.9409**	**1137.5513**	**−566.0151**	**1138.0302**	**1138.0451**	**1141.6555***
Log-logistic	−573.8956	1153.7912	1153.8061	1157.4165	−573.1456	1152.2912	1152.3061	1155.9165
Gamma	−577.6341	1161.2682	1161.2831	1164.8935	−579.5686	1165.1372	1165.1521	1168.7625
Exponential	−658.8353	1321.6706	1321.6780	1324.0874	−659.3852	1322.7704	1322.7778	1325.1873
Lognormal	−584.6854	1175.3708	1175.3857	1178.9961	−585.6226	1177.2452	1177.2601	1180.8705

The model with the * is the best fit model (least AIC, AICc and BIC values).

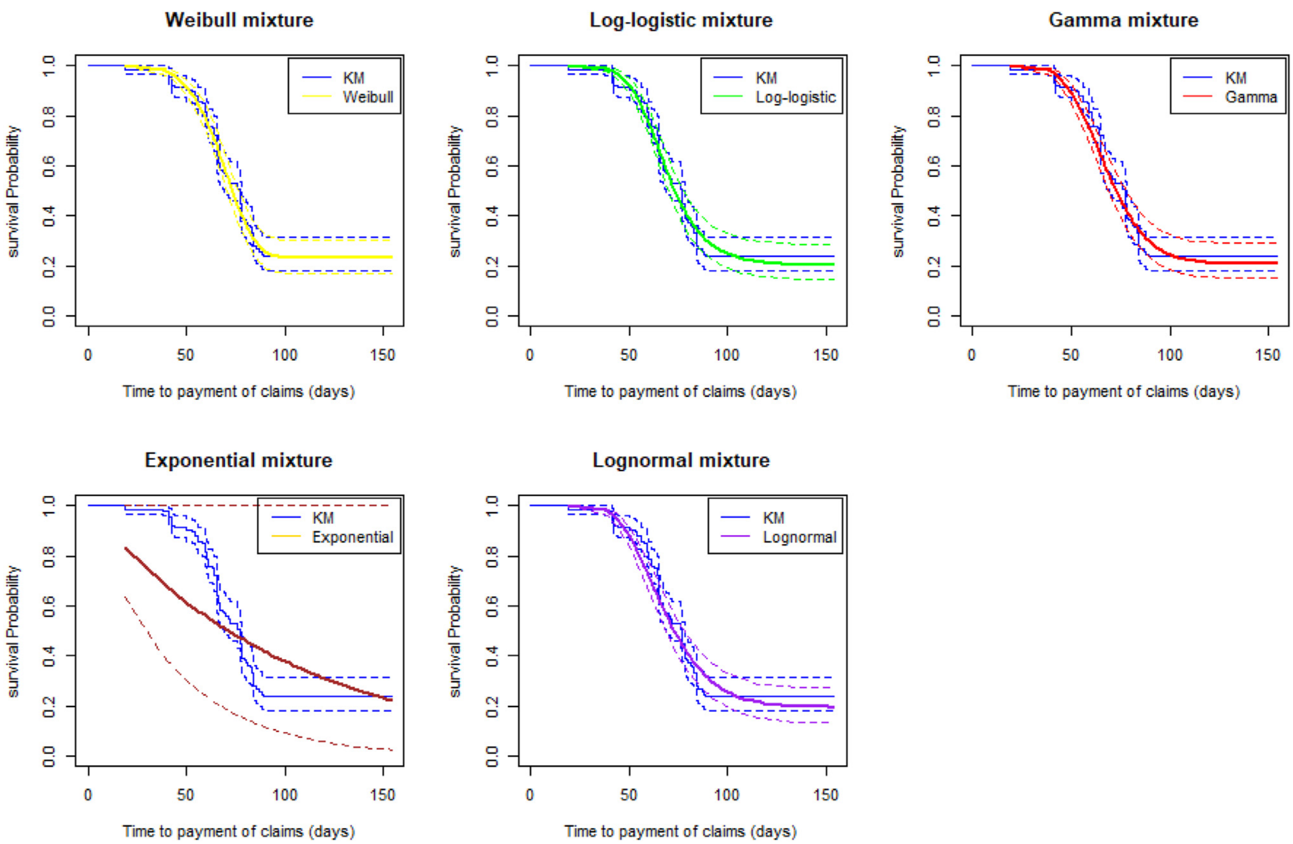

Fig. 4. Fitted mixture cure rate models.

mixture cure rate model fits the claims payment survival times best as the curve of the Weibull mixture cure model is closer to the Kaplan–Meier curve than the curves of the other competitive mixture cure rate models. Thus, the Weibull mixture cure rate model is the best model to be applied for modelling the claims payment survival data.

To compare the fit of the non-mixture cure rate models, the estimated survival curves from the non-mixture cure rate models are presented with the Kaplan–Meier curve as shown in Fig. 5. The Weibull non-mixture cure rate model fits the claims payment survival data best as the curve of the Weibull non-mixture cure rate model is closer to the Kaplan–Meier curve than the curves of the other competitive non-mixture cure rate models. Thus, the Weibull non-mixture cure rate model is the best model to be applied for modelling the claims payment survival data.

3.3. Cure rate models with covariates

The mixture and non-mixture cure rate regression models are fitted to the claims payment survival data with covariates including length of vetting of claims ($\widehat{\beta}_1$), the number of NHIA staff vetting the claims ($\widehat{\beta}_2$) and the category of claims submission ($\widehat{\beta}_3$) to investigate the effect of these covariates on the claims payment cured rate. Table 4 presents the

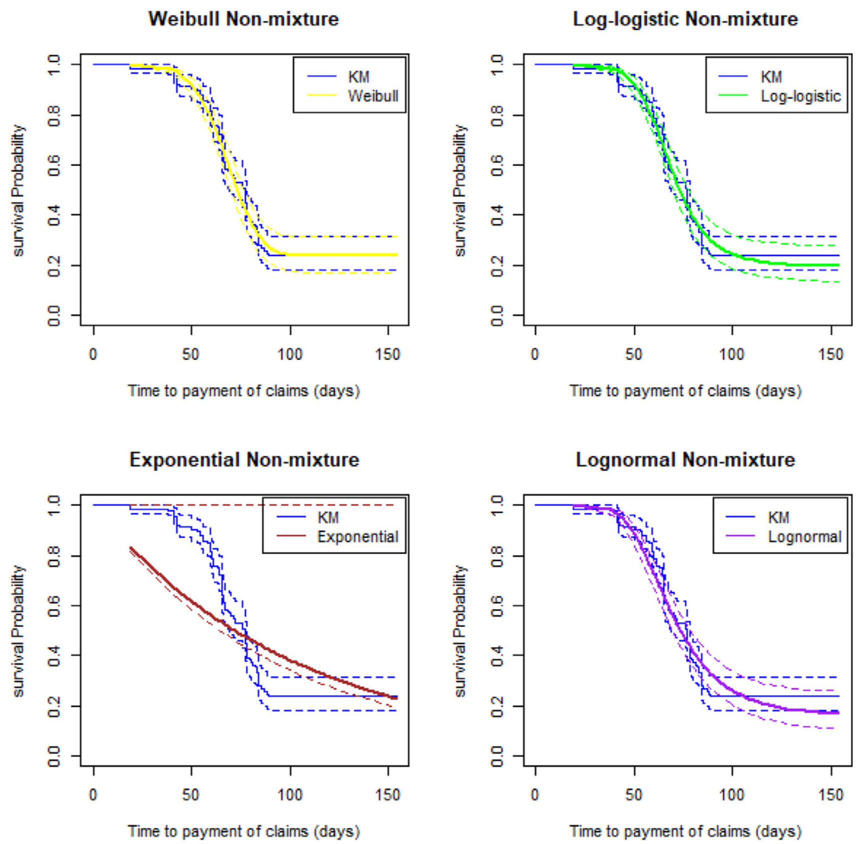

Fig. 5. Fitted non-mixture cure rate models.

Table 4. Parameter estimates of cure rate models with covariates.

Model	Parameter	Mixture			Non-Mixture		
		Estimate	Std Error	95% CI	Estimate	Std Error	95% CI
Weibull	$\hat{\zeta}$	5.7397	0.4529	(4.8521; 6.6273)[a]	6.6004	0.5153	(5.5904; 7.6104)[a]
	$\hat{\beta}_0$	72.5583	1.2549	(70.0986; 75.0179)[a]	80.3771	1.9389	(76.5768; 84.1773)[a]
	$\hat{\beta}_1$	−0.0352	0.0247	(−0.0837; 0.0132)	−0.0278	0.0209	(−0.0688; 0.0132)
	$\hat{\beta}_2$	0.6017	0.1620	(0.2842; 0.9192)[a]	0.5764	0.1284	(0.3247; 0.8281)[a]
	$\hat{\beta}_3$	−2.4312	0.7776	(−3.9553; −0.9071)[a]	−3.1542	0.7382	(−4.6011; −1.7072)[a]
Log-logistic	$\hat{\zeta}$	7.1524	0.6216	(5.9340; 8.3707)[a]	6.9389	0.6209	(5.7219; 8.1558)[a]
	$\hat{\beta}_0$	68.2429	1.5344	(65.2354; 71.2503)[a]	80.5576	2.9684	(74.7396; 86.3756)[a]
	$\hat{\beta}_1$	−0.0421	0.0305	(−0.1018; 0.0177)	−0.0340	0.0237	(−0.0804; 0.0124)
	$\hat{\beta}_2$	0.7961	0.2725	(0.2620; 1.3302)[a]	0.6815	0.1574	(0.3731; 0.9900)[a]
	$\hat{\beta}_3$	−2.8617	1.2537	(−5.3190; −0.4044)[a]	−3.6266	0.8987	(−5.3881; −1.8651)[a]
Gamma	$\hat{\zeta}$	15.6427	2.2286	(11.2746; 20.0107)[a]	13.2971	2.0909	(9.1988; 17.3954)[a]
	$\hat{\beta}_0$	0.2286	0.0342	(0.1615; 0.2958)[a]	0.1548	0.0315	(0.0932; 0.2165)[a]
	$\hat{\beta}_1$	−0.0410	0.0293	(−0.0984; 0.0163)	−0.0357	0.0250	(−0.0848; 0.0133)
	$\hat{\beta}_2$	0.7681	0.2529	(0.2722; 1.2639)[a]	0.7098	0.1789	(0.3591; 1.0604)[a]
	$\hat{\beta}_3$	−2.6235	0.9818	(−4.5478; −0.6993)[a]	−3.6959	0.9887	(−5.6337; −1.7580)[a]
Exponential	$\hat{\beta}_0$	0.0115	0.0012	(0.0091; 0.0139)[a]	0.0002	0.0002	(−0.0002; 0.0006)
	$\hat{\beta}_1$	−0.1020	0.0802	(−0.2592; 0.0552)	−0.5220	0.6240	(−1.7450; 0.7010)
	$\hat{\beta}_2$	1.6700	1.9100	(−2.0736; 5.4136)	−7.5200	6.3200	(−4.8672; 19.9072)
	$\hat{\beta}_3$	−9.1900	36.7000	(−81.1220; 62.7420)	−39.1000	36.2000	(−110.0520; 31.8520)
Lognormal	$\hat{\zeta}$	4.2047	0.0282	(4.1493; 4.2600)[a]	4.5324	0.0925	(4.3510; 4.7138)[a]
	$\hat{\beta}_0$	0.2822	0.0211	(0.2408; 0.3236)[a]	0.3506	0.0386	(0.2750; 0.4262)[a]
	$\hat{\beta}_1$	−0.0447	0.0323	(−0.1080; 0.0185)	−0.0436	0.0297	(−0.1017; 0.0146)
	$\hat{\beta}_2$	0.8560	0.3120	(0.2445; 1.4675)[a]	0.8621	0.2565	(0.3593; 1.3649)[a]
	$\hat{\beta}_3$	−2.9667	1.4219	(−5.7538; −0.1797)[a]	−4.4626	1.4044	(−7.2153; −1.7099)[a]

[a] Implies significant at 5% significance level.

estimates of the parameters of the cure rate models, their corresponding standard errors and 95% confidence interval (CI) estimates. It can be seen that all the parameters and the covariates for both mixture and non-mixture models except covariates claims length of vetting $(\widehat{\beta}_1)$ are significant at 5% significance level since the CI estimates of the models do not contain zero. However, all the parameters of the exponential cure rate model for both mixture and non-mixture models are not significant at 5% significance level since the CI estimates of the models contain zero. This implies that, the covariates, number of NHIA staff vetting the claims $(\widehat{\beta}_2)$ and claims submission category $(\widehat{\beta}_3)$ contribute to the claims payments being cured or uncured but the covariate, claims length of vetting $(\widehat{\beta}_1)$ does not contribute to the probability of claims payment being cured or uncured. Hence, the covariate, number of staff vetting the claims contributes directly to the probability of claims payment being cured while it contributes inversely to the probability of claims payment being uncured. Thus, high staff strength is related to high cured claims payment. The results also revealed that, the claims submitted on time have less probability of not being cured than the claims submitted late. Therefore, the claims submitted on time have higher probability of claims payment being uncured compared to the claims submitted late. This confirms the reason why the NHIA has adopted initiatives such as consolidated claims processing centers with requisite staff, electronic processing of claims among others to improve claims management especially to reduce the claims processing turn-around time for the sustainability of the scheme [23]. The estimated value of the shape parameter $(\widehat{\zeta})$ of the cure models depicts the behaviour of the cure rate $\widehat{p}$ of the claims payment survival times. This reveals that the cure rate $\widehat{p}$ increases over time as the shape parameter $(\widehat{\zeta})$ values of all the cure models are greater than one $(\widehat{\zeta} > 1)$. This confirms the results obtained in Table 2.

The main problem to be addressed is to identify the appropriate cure rate model underlying the claims payment survival data which can take into account the covariates effects on the cured proportion. Therefore, Table 5 shows the model comparison criteria employed to select the model that best fit the claims payment survival data with the covariates effects. Thus, both Weibull mixture and non-mixture cure rate models have the largest values of log-likelihood (ℓ) and least values of AIC, AICc and BIC when compared to the other competitive models. Consequently, Weibull cure rate model is the best fit model that can be used as baseline model to model the claims payment survival data over the other competitive models. This is however expected as the data shows the characteristics of heavy tail distribution as observed in the positive excess kurtosis value in Table 1. These results are also similar to the results obtained in Table 3 except that the estimated values of the information criteria are different due to parameterization.

To compare the fit of the mixture cure rate regression models, the estimated survival curves from the mixture cure rate models with covariates effects are presented and overlaid with Kaplan−Meier curve as can be observed in Fig. 6. The Weibull mixture cure rate regression model fits the claims payment survival data best as the curve of the Weibull mixture cure model is closer to the Kaplan−Meier curve than the curves of the other competitive mixture cure rate models. This confirms the results in Table 5 and the plot obtained in Fig. 4. Thus, the Weibull mixture cure rate model is the best model to be applied for modelling the claims payments survival data with covariates.

To compare the fit of the non-mixture cure rate models on the claims payment survival times, Fig. 7 shows non-mixture cure rate models with covariates effect and Kaplan−Meier curve. The Weibull non-mixture cure rate model fits the claims payment survival times best as the curve of the Weibull non-mixture cure rate model is closer to the Kaplan−Meier curve than the curves of the other competitive non-mixture cure rate models. This confirms the results in Table 5 and the plot obtained in Fig. 5. Thus, the Weibull non-mixture cure rate

Table 5. Information criteria of cure rate models with covariates.

Model	Mixture				Non-mixture			
	ℓ	AIC	AICc	BIC	ℓ	AIC	AICc	BIC
Weibull	**−548.6653**	**1109.3306**	**1109.3828**	**1116.5812**	**−543.9517**	**1099.9034**	**1099.9556**	**1107.1540***
Log-logistic	−558.0589	1128.1178	1128.1700	1135.3684	−549.9178	1111.8356	1111.8878	1119.0862
Gamma	−561.7986	1135.5972	1135.6494	1142.8478	−557.1633	1126.3266	1126.3788	1133.5772
Exponential	−654.3279	1318.6558	1318.6931	1324.6980	−649.3144	1308.6288	1308.6661	1314.6710
Lognormal	−568.6818	1149.3636	1149.4158	1156.6142	−562.4591	1136.9182	1136.9704	1144.1688

The model with the * is the best fit model (least AIC, AICc and BIC values).

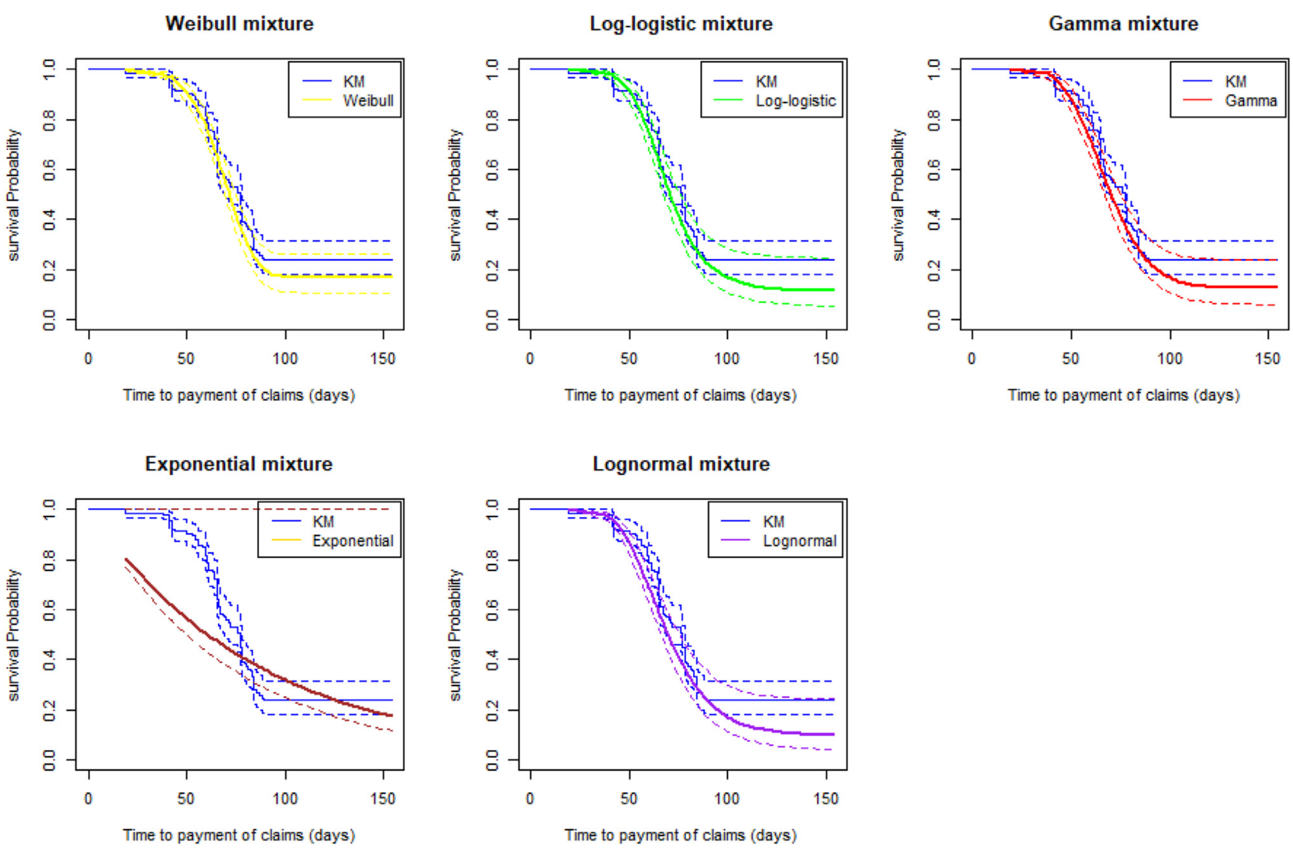

Fig. 6. Fitted mixture cure rate models with covariates.

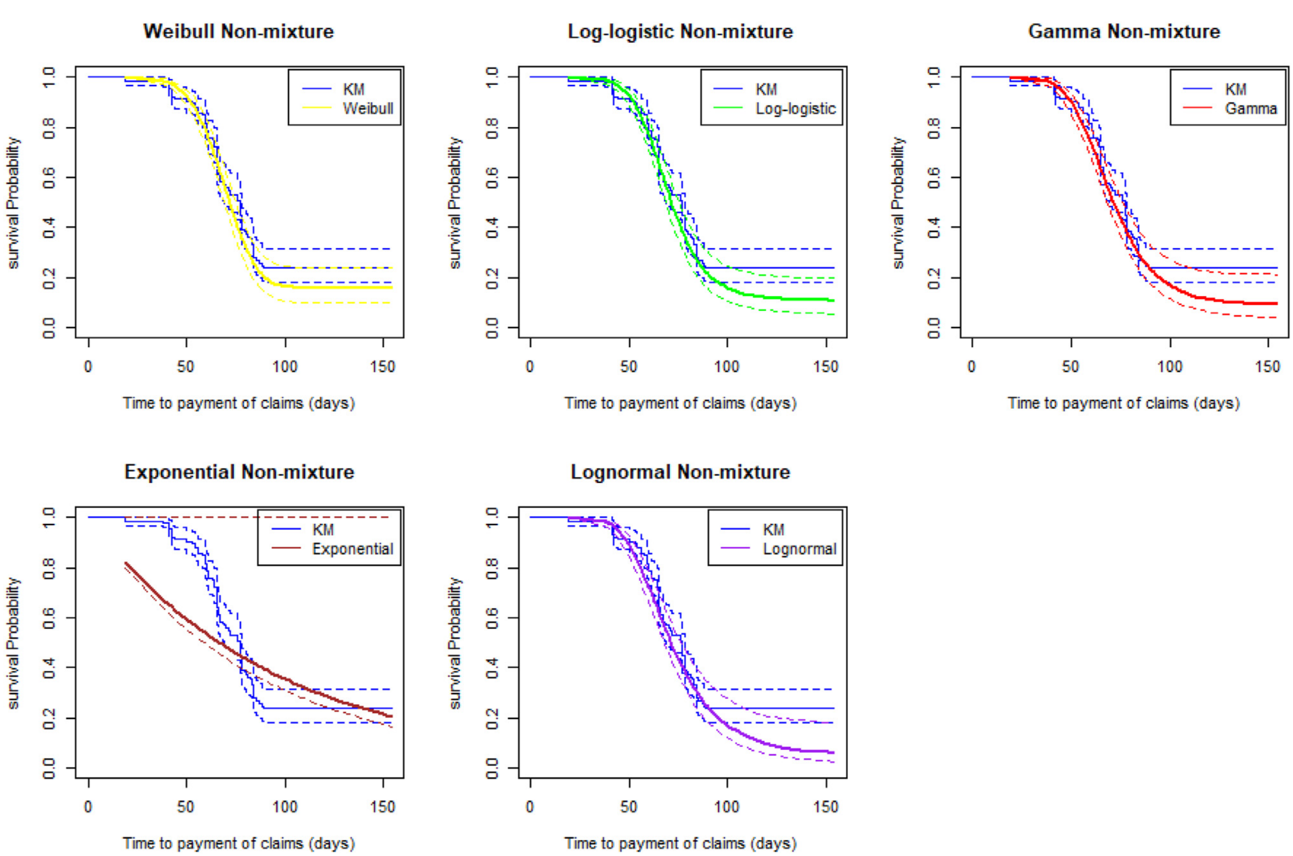

Fig. 7. Fitted non-mixture cure rate models with covariates.

model is the best model to be applied for modelling the claims payment survival data.

4. Conclusions

In this study, cure rate models have been applied to model National Health Insurance Scheme (NHIS) claims payment data with cured proportion using Pru District in the Bono East Region of Ghana as a case study. The covariates effects were also modelled to investigate the effects of the covariates on the cured proportion. The estimates of the parameters of the models were obtained by directly maximizing the observed likelihood function. Most estimates of the parameters of the cure models are significant at 5% significance level. The study revealed that the cured claims payments rate increases over time with an estimated cured rate of 23.2% whereas the uncured claims payments rate was 76.8%. Most covariates are significant at 5% significance level in most of the cure rate regression models, thus, the covariates, number of NHIA staff vetting the claims and claims submission category contribute to the claims payments cure rate. Moreover, both Weibull mixture and non-mixture cure rate models modelled the claims payment survival data with cured proportion best over the other competitive models. Therefore, to ensure the sustainability of the scheme and to prevent the return of cash and carry system with its adverse effects on the residents of Ghana and to attain the UHC by the year 2030 in Ghana, the stakeholders should consider prioritising claims payments to the HCPs at the PHC levels within the regulated time frame over the secondary and the tertiary HCPs. More so, to model the claims payment data efficiently, further research work may consider developing efficient cure rate models over the existing models.

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