A logistic regression model for Ghana National Health Insurance claims

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ABSTRACT

In August 2003, the Ghanaian Government made history by implementing the first National Health Insurance System (NHIS) in Sub-Saharan Africa. Within three years, over half of the country's population had voluntarily enrolled into the National Health Insurance Scheme. This study had three objectives: 1) To estimate the risk factors that influences the Ghana national health insurance claims. 2) To estimate the magnitude of each of the risk factors in relation to the Ghana national health insurance claims. In this work, data was collected from the policyholders of the Ghana National Health Insurance Scheme with the help of the National Health Insurance database and the patients' attendance register of the Koforidua Regional Hospital, from 1st January to 31st December 2011. Quantitative analysis was done using the generalized linear regression (GLR) models. The results indicate that risk factors such as sex, age, marital status, distance and length of stay at the hospital were important predictors of health insurance claims. However, it was found that the risk factors; health status, billed charges and income level are not good predictors of national health insurance claim. The outcome of the study shows that sex, age, marital status, distance and length of stay at the hospital are statistically significant in the determination of the Ghana National health insurance premiums since they considerably influence claims. We recommended, among other things that, the National Health Insurance Authority should facilitate the institutionalization of the collection of appropriate data on a continuous basis to help in the determination of future premiums.

Keywords: National Health Insurance, Claims, Logistic Regression, Odds Ratio, Ghana.

1. Introduction

In most African and South American countries, economic problems have resulted in decreased government funding of the health sector and reduced access to health care for most of the population. For example in Nigeria, the public spending per capita for health is less than $5 and can be less than $2 in poorer parts of the country (WHO 2006). Situations like this have prompted governments of low income countries to explore alternative forms and sources of health sector financing. In many European countries social health insurance is one of the principal methods of health financing and has a long history (Carrin et al. 2004).

"One programme which all the major political parties in Ghana have openly agreed upon, though with different approaches, is the implementation of the National Health Insurance Scheme" (Daily Graphic May 17, 2005). The financial performance of an Insurance Scheme is a function of the premium collected, the cost of health care services of the insured, the level of external subsidy, the size of the pool, and degree of economies of scale that is achieved (Aikins, 2004).

The probability and claim size forecast is very important, since an insurance company can use these estimates to offer or not offer premium discounts depending on an individual client's characteristics or create strategies for detecting fraudulent claims (Viaene et al, 2007). Insurance companies need to treat risk management as a series of related factors and events (Meulbroek, 2001). In order to handle claims arising from incidents that have already occurred insurers must employ predictive methods to deal with the extent of this liability (Boland, 2007). Therefore, an insurance company has to find ways to predict claims and appropriately charge a premium to cover this risk.

Insurers have to look for better ways to capture the characteristics of individuals that affect claim size and probability, and consequently identify insured persons that have a higher propensity for generating losses.

Insurance companies attempt to estimate reasonable prices for insurance policies based on the losses reported for certain kinds of policy holders. This estimate has to consider past data in order to grasp the trends that have occurred (Weisberg and Tomberlin, 1982).

According to World Health Organization in 2006, about 1.3 billion people in the world lack access to effective and affordable health care due to financial limitations or governments inability to provide the necessary coverage. For instance, the United Nation Development Programme (UNDP) report for the year 2007 (UNDP, 2007:32-33), estimates that about 70 percent of the population of Ghana use alternative medicine which includes traditional health care while 30 percent use orthodox medical care. The report further posits that in terms of orthodox health care in Ghana, only 18.4 percent of the sick or injured consulted a health practitioner and a sizeable proportion of rural areas and northern Ghana generally are excluded due to the inability to pay. The Millennium Development Goals for poverty reduction and health will not be met without a concerted effort aimed at extending health interventions to the world's poor (Sachs et al, 2001:29). Against this background, the Ghanaian parliament in 2003 passed the National Health Insurance (NHI) Act, Act 650 promoting Mutual Health Insurance Schemes for the extension of social protection in health to the poor regardless of ability to pay at the point of accessing health services. This culminated in the official launch of the National Health Insurance Scheme (NHIS) in March 2005. The scheme gives prominence to community/district mutual health insurance schemes as a key strategy for the extension of social security in health to every Ghanaian in a bid to enhance access to health care especially for the rural poor and combat social exclusion. There have also been debates about the levels of premium being collected currently by the Scheme. One School of thought have it that if premiums are not increased from the current levels, the scheme may run into severe financial difficulties due to high level of claims.

In this study we looked into some of the problems enumerated above and critically examine some important characteristics of national health insurance policy holders. We addressed the issues of the views and attitudes of the National Health Insurance Authority (NHIA) regarding estimation of national health insurance claims as well as factors that the authority consider in premium rating. Again, the paper contributed to the existing literature on national health insurance studies in Ghana by providing empirical results pertaining to the significant effect of policyholders' risk factors on claim made or otherwise. It is believed that results would have implications for the successful implementation of national health insurance policies in Ghana.

In order to achieve the aim of the study, the binary logit model was employed. The choice of this statistical technique is based on the dichotomous nature of the response variable (whether a policy holder has made claim or not).The data of the study was drawn from the NHIA data base and the hospital records of the Koforidua regional hospital. The remaining part of the paper is organized as follows: section 2 describes the concept of the methods employed in the research. The data, empirical analysis, and results are presented in section 3; the discussions are presented in section 3. Section 4 provides the concluding remarks as well as recommendations.

2. Methods

2.1 Study Area and Source of Data

The eastern region of Ghana has 21 administrative Municipals and Districts with Koforidua as the regional capital. Eastern Region of Ghana has an estimated population of 2,194,508, with 3.1% growth rate. It is the sixth largest region with a land area of 19,323 sq. km., thus representing about 8% of the total land area of the country (Statistical Service, 2011). The region is bounded on the East by the Volta Region, South by Greater Accra region, West by Central Region and on the North by Ashanti Region. It has the largest number of health facilities in the country. The Koforidua Regional Hospital is a state run referral hospital. The hospital, with about 250 patient beds is the largest facility in the region which serves both as the first consultation point for patients within its catchment, and as a referral centre for about other 25 primary health centers. These facilities are managed by the Ministry of Health and the Ghana Health Service.

2.2 Data collection and data management

Data used in this study were obtained as primary data from hospital attendance records at the Koforidua Regional Hospital, from 1st January 2011 to 31st December 2011. Data was collected from the policyholders of NHIS in Ghana using the simple random sampling technique with the help of the NHIA database. A total of 4549 policyholders were sampled from the NHIA data base. For this study, the hospital attendance register was used which has patients' age, sex, date of admission and discharge, insurance claim or otherwise, location of residence, billed charges (i.e. for treatment), marital status, health status and whether the patient was an outpatient or inpatient. Income levels were obtained from the health insurance data base. From the data, the following variables were coded:

outcome (claim = 1, no claim = 0); *length of stay* (inpatient=1, outpatient = 0); *marital status* (married = 1, unmarried = 0); *distance* to the hospital ((distance > 5km) = 1, (distance ≤ 5km) = 0).

The distance of 5 km was chosen to reflect travel time of 1 hour on foot. Age, sex, health status, income level, and billed charges were employed as deciding factors.

2.3 Model specification, estimation and tests

The response variable in logistic regression is usually dichotomous, that is, the response variable can take the value 1 with a probability of success *p*, or the value 0 with probability of failure, (*1-p)*. To explain the logistic regression, we show here the logistic function *f (z)*, which describes the mathematical form on which the logistic model is based

$$f(z) = \frac{1}{1+e^{-z}} \qquad (1)$$

Where *z* denotes the values of this function, such that, $-\infty \leq z \leq +\infty$. The relationship between the predictor and response variables is not a linear function in logistic regression; instead, the logistic regression function is used, which is the *logit* transformation of *p*. To obtain the logistic model from the logistic function, we write *z* as the linear sum.

$$z = \alpha + \sum_{i=1}^{k} \beta_i x_i \qquad (2)$$

Where x_i are independent variables of interest and *α* and β_i are constant terms representing unknown parameters and *k* is the last term. Combining (1) and (2) gives:

$$f(z) = \frac{1}{1+e^{-\left(\alpha + \sum_{i=1}^{k} \beta_i x_i\right)}}$$

For notational convenience, we will denote the probability statement as simply *p(x)* where *x* is a notation for the collection of variables x_1 through x_k. Thus, the logistic model may be written as

$$f(X) = \frac{1}{1+e^{-\left(\alpha + \sum_{i=1}^{k} \beta_i x_i\right)}} \qquad (3)$$

However, since the above logistic model is non-linear function, the *logit* transformation would be used to make it linear.

$$Logit(X) = In_e\left(\frac{P(x)}{1-P(x)}\right) \qquad (4)$$

Where, $$P(x) = \frac{1}{1+e^{-\left(\alpha + \sum_{i=1}^{k} \beta_i x_i\right)}}$$

This transformation allows us to compute a number, *logit p(x)*, for an individual with independent variables given by *x*.

Logit $P(x) = \alpha + \sum_{i=1}^{k} \beta_i x_i$ (5)

Thus, the logit of *p(x)* simplifies to the linear sum. The quantity *p(x)* divided by *1-p(x),* whose *log* value gives the *logit,* describes the odds for a policyholder not making a claim, with independent variables specified by *x.*

$\frac{P(x)}{1-P(x)} =$ *Odds for individual X*

The goal of logistic regression is to correctly predict the category of outcome for individual cases using the most parsimonious model. To this end, a model is created that includes all predictor variables that are useful in predicting the response variable (Kleinbaum and Klein, 1994). For this study, the risk of making an insurance claim are influenced by predictors such as age, distance, billed charges, sex, marital status, length of stay, health status and income level . The following logistic regression model was fitted to the data.

$$Logit(P(y=1)) = \beta + \varepsilon + \sum_{i=1}^{k=8} \beta_i x_i \qquad (6)$$

Where *P* is the probability of claim made, the *x*'s are independent variables of interest, *α* and the β_i are constant term and coefficients respectively representing unknown parameters and *ε* is the residual term. The coefficients of the model predictors are tested via the hypothesis as follows:

$$H_o: \beta j = 0$$

$H_i: \beta j \neq 0$ *j = 1, 2,3,4,5,6,7,8*

Once a logistic regression model has been fit to a given set of data, the adequacy of the model is examined by overall goodness-of-fit tests and examination of influential observations. One concludes a model fits if the differences between the observed and fitted values are small and if there is no systematic contribution of the differences to the error structure of the model. A goodness-of-fit test that is commonly used to assess the fit of logistic regression models is the Hosmer–Lemeshow test (Hosmer and Lemeshow, 1980). Although appropriate estimation methods which take into account the sampling design in estimating logistic regression model parameters are available in various statistical packages, there is a corresponding absence of design-based goodness-of-fit testing procedures. Due to this noted absence, it has been suggested that goodness-of-fit be examined by first fitting the design-based model, then estimating the probabilities, and subsequently using iid-based tests for goodness-of-fit and applying any findings to the design-based model (Hosmer and Lemeshow, 2000). The hypothesis for model fitness can be measured by the *Hosmer and Lemeshow test* as follows

H_o: *The model fits the data*
H_i: *The model does not fit the data*

3.0 Empirical Results

Table 1, shows the number of observations for the study. The total number of observations for this study was 4549. More than 50% of the people who were sampled were females (56.0%) and the rest (44.0%) were males. The table indicates the frequency of the respondents who made or did not make a claim. Majority of the respondents have made an insurance claim (92.0%), the rest have not made claims in the year (8.0%). The results indicates that majority of the respondents (46.3%) are in the age group of 18-39 years, followed by the age group 40-60 years (19.4%), the rest are in the age groups of 0-17 and 61-100 (19.2% and 15.1%) respectively. The results indicate that majority of the policyholders who made claims are among the working group aged between 18-39 years (45.2%). The results show that majority of the respondents were unmarried (58.7%) and the rest are married (41.3%).Table 1 shows that majority of the policyholders sampled have very good or good health status (65.3%), (24.0%) of the policyholders had fair health status and the rest had poor health status (10.7%). Again, majority of the patients that attended hospital are charged bills between GHS1-400 (58.6%), (26.2%) of the policyholders that attended hospital were billed between GHS 401-800, the rest were billed GHS 801 or more (9.7%).Majority of the policyholders who were sampled earned incomes between GHS1-1000 (54.0%), (31.4%) of the policyholders earned no income and the rest earned GHS1001 or more (14.6%). Majority of the policyholders travel less or equal to 5km to the hospital (51.2%), and the rest travel more than 5km to the hospital. Majority of the sampled policyholders used outpatient services at the hospital (57.2%), and (36.8%) used inpatient services and the rest (6.0%) had not used the hospital services in the year.

Table 1: Composition of the survey population

Age(Years)	**Numbers**	**%**
0-17	873	19.2
18-39	2105	46.3
40-60	884	19.4
61-100	687	15.1
Sex	**Numbers**	**%**
Male	2002	44.0
Female	2547	56.0
Marital Status	**Numbers**	**%**
Married	1879	41.3
Unmarried	2670	58.7
Health Status	**Numbers**	**%**
Very Good	1165	25.6
Good	1805	39.7
Fair	1092	24.0
Poor	487	10.7
Billed Charges	**Numbers**	**%**
No	250	5.5
GHS 1-400	2666	58.6
GHS 401-800	1191	26.2
GHS 801-1200	246	5.4
GHS 1201-1600	123	2.7
>GHS 1600	73	1.6
Income Level	**Numbers**	**%**
No income	1429	31.4
GHS 1-1000	2456	54.0
GHS 1001-2000	600	13.2
GHS 2001-3000	59	1.3
GHS>3000	5	0.1
Distance	**Numbers**	**%**
> 5km	2220	48.8
$\leq$ 5km	2329	51.2
Length of Stay	**Numbers**	**%**
Non	273	6.0
Claim	**Numbers**	**%**
Yes	4185	92.0
No	364	8.0

3.1 Odds Ratio Analysis of Risk Factors

The computation of the crude odds ratio for risk factors, *X,* is given by the estimate *Exp (B).* The crude odds ratio of risk factor determines the influence it has on the claim outcome. The Wald's and log likelihood ratio tests are also performed to ascertain the significant effect of the risk factors. A probability value of less than or equal to 0.05 was considered to be statistically significant. Hence the inclusion of that risk factor is important in determining the claims outcome Y=0 or 1

Table 2: Logistic Regression Predicting Likelihood of Health Insurance Claim

Variable	B	S.E.	Wald	df	P-Values	Odds Ratio
Sex	0.591	0.140	17.688	1	0.000	1.805
Age	-0.290	0.069	17.787	1	0.000	0.748
Marital Status	0.404	0.193	4.376	1	0.036	1.498
Health Status	0.168	0.131	1.650	1	0.199	1.183
Billed Charges	0.744	0.389	3.660	1	0.056	2.104
Income Level	0.364	0.243	2.242	1	0.136	1.439
Length of Stay	-5.620	0.521	116.294	1	0.000	0.004
Distance	0.617	0.260	5.630	1	0.018	1.853
Constant	3.036	0.330	84.459	1	0.000	20.828

The parameters of the model were estimated using maximum likelihood approach. The estimates for each independent variable are interpreted relative to the referenced category. The estimated odds ratio for all parameters is presented in table 2.

The working group (18-40 years) is 0.748 more likely to make a claim compared to children (1-17 years) with 95% confidence interval (p-value=0.000) is statistically significant. The odds ratio of 1.805 and a confidence interval of 95%, indicates that females are 1.805 as likely to make a claim compared to their male counterparts, giving a similar statistically significant results. Unmarried policyholders are 1.748 as likely as their married counterparts to make insurance claim at 95% confidence interval (p-value=0.036).Similarly the results indicates that the odds of making an insurance claim increases by a factor of 1.853 with a confidence interval of 95% when the policyholder travels less than or equal to 5km to attend to the hospital (p-value=0.018). Table 2 shows an odds ratio of 0.004 indicating that, inpatients make 0.004 insurance claims as likely as their outpatients' counterparts with 95% confidence interval (p-value=0.000) controlling for other factors in the model. The results suggest a non-negligible effect (p-value=0.056) of the billed charges to influence health insurance claims.

Health status and income level had probability values of more than 0.05, which means that the health status and income level predictor variables are not significant with 95% confidence interval. The logistic regression obtained was as follows (see Table 2 above):

$$\begin{aligned} Logit\big(P(y=1)\big) = 3.036 + 0.591Sex - 0.290Age + 0.404Marital\ Status + 0.168Health\ Status \\ + 0.744Billed\ Charges + 0.364Income\ Level - 5.620LengtH\ of\ Stay\ + 0.617Distance \end{aligned}$$

It is noted that, the risk factors; sex, age, marital status, Length of stay and distance are significant at α = 0.05 with their respective significance values equal to 0.000, 0.000, 0.036, 0.000 and 0.018. Therefore, these risk factors are relevant in predicting national health insurance claims in Ghana. From Table 2, it is revealing to note that, the risk factors- health status, billed charges and income level are not **statistically** significant when the other factors are held constant.

Table 3 indicates that the *P– value* of the Hosmer and Lemeshow test (0.145) is greater than the significance level of 0.05. It can be concluded that there is enough evidence that the hypothesized model fits the data well. This indicates that the risks factors for making an insurance claim may not be significantly different from those used in the postulated model

Table 3: Assessing Model Fit by Hosmer and Lemeshow Test.

Chi-Square	*df*	*P-Value*
11.432	9	0.145

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4. Discussions

The study provides evidence of the risk factors which influences Ghana national health insurance claims, in the eastern region of Ghana. The model indicates that distance contributes more, among other factors, in terms of influencing policyholders making health insurance claims in Ghana. Thus the further the town is from the health centre, the more disadvantaged the policyholders are in terms of getting early health care and making an insurance claim.

The study showed that patients within 5 km of hospital were more likely to make an insurance claim than those beyond 5km, and does reflect the fact that nearness to the hospital improved early access to care. It was also observed that females were at higher chance of making an insurance claim compared to their male counterparts, after adjusting for distance and other risk factors. This suggests that more females access health care services more than males. With regard to the age of policyholders, there was inverse relationship with health insurance claims. Hence, as people grow the risk of making an insurance claim reduces. This suggests that by and large younger people access health care more than older people.

This study provides evidence that health insurance claims, in the eastern region of Ghana could be described as high. One major shortcoming of using this data is that they only represent those patients who visited the Koforidua regional hospital. Meanwhile, some policyholders may have sought care in other health facilities in the region.

5. Conclusion

The study indicated that children and the working group (0-39 years) have a higher risk of making health insurance claims. The findings showed risk factors such as sex, age, marital status, distance and length of stay at the hospital were significantly contributing to national health insurance claims. However, risk factors such as health status, billed charges and income level were not significant contributing risk factors to the national health insurance claims. The government should consider building more health centers, clinics and cheap-compounds in at least every community, to help reduce the travel time in accessing health care. The ministry of health and the Ghana health service should engage older citizens by encouraging them to use hospitals when they are sick instead of other alternative care providers.

The Ghana National Health Insurance Scheme is on course. Much more needs to be done beyond what currently pertains, for the appropriate determination of premiums for Health Insurance in Ghana; since the sustainability and credibility of the health insurance industry is dependent on getting it right so far as the determination of premiums is concerned. This can be facilitated by institutionalizing the collection of appropriate data on a continuous basis, to assist this important area of the industry's administration, and all effort must be made in this direction if success is envisaged.

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