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Statistical Analysis of Health Insurance and Cash and Carry Systems in Cape Coast Teaching Hospital of Ghana

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Abstract: The passage of National Health Insurance Scheme to replace the old system (called cash and carry) in Ghana seems to have raised many questions as to whether it has increased the rate at which people attend hospital and abolished cash and carry system. The data collected were hospital attendance for both health insurance and cash and carry system on monthly basis across age groups and gender for 2008-2017, obtained from Cape Coast Teaching Hospital. Chi-Square tests and the Box-Jenkins's methodology of time series analysis were employed to analyse the data. From the findings, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plot suggested an AR process with order 1. Candidate models were obtained using the minimum AIC criteria to select adequate models and appropriate models were obtained as SARIMA (1,0,0) $(0,1,0)_{12}$ model for insured (NHIS) and SARIMA (1,1,1) $(2,0,1)_{12}$ model for uninsured (Cash and Carry system). Model diagnostics tests were performed using Ljung-Box test. The Chi-square tests inferred dependence in hospital attendance between insured and non-insured patients on gender and the years, In conclusion, insured patients will be increasing throughout the age groups and non-insured patients will be increasing for specific age groups 0-28 days to 15-17 years for the next 24 months. This research recommended among others that education should be given to the general public about the importance of health insurance, it registration and operations especially age group 0-28days to 15-17 years because they seem to continue the use of Cash and Carry System in seeking healthcare regardless of the introduction of NHIS.

Keywords: Box-Jenkins, NHIS, Cash Carry, Hospital Attendance, Chi-Square

1. Introduction

Time series methodology have been applied in diverse fields, namely; engineering, epidemiological studies, Education and Health. Bannor et. al. (2012) [1] developed an ARIMA model for hospital attendance in Obuasi, Ghana. Retrospective monthly data spanning from January, 2008 to December, 2011 from the Obuasi Government Hospital was used. From the analysis, ARIMA (2, 1, 0) was selected as the best model with the smallest AIC of 420.33. The forecasting results in general revealed a stabilized trend of OPD attendance over the forecasted period and turning point at the month of January, 2012.

Arthur (2013) [2] did a time series study of OPD attendance at the Saltpond Municipal Hospital. He used a retrospective data from 2002 to 2012. SARIMA (1, 1, 3) (0, 1, $1)_{12}$ was the best model fit. The five year forecast showed an increasing trend in cases.

Abubakari (2012) [3] also developed an ARIMA models for NHIS hospital enrolment in the Northern region of Ghana and used the best fit model to forecast for 2011 and 2012. The predicted values recorded were decreasing from month to month. Other findings showed that enrolment of patients to the scheme had experienced an increase and a decrease linear trend from the year 2005 to 2010. The highest enrolment (4, 213) from the inception of the scheme was recorded in December 2008. Thereafter, enrolments have been declining gradually from year to year. However, most of other few high enrolment values were recorded from August to December over the period under study and same was seen from the predicted values of 2011 and 2012.

In Ghana, the National Health Insurance Scheme established by the government and enacted by ACT 650 of the NHI ACT replaced the old system of payment of hospital bills, popularly known as 'Cash and Carry' (payment of hospital bills without insurance cover) where patients pay physical money for their hospital bills without any insurance cover [4]. After over a decade of the implementation of NHIS bill, it is very important to compare the trend of hospital attendance using either of the two. This research sought to investigate whether the introduction of the National Health Insurance has increased attendance in the hospitals over Cash and Carry system using time series and chi-square analyses.

2. Method

The research was restricted to Cape Coast Teaching Hospital in the Central Region of Ghana. The target population for the study was patients who attend hospital with health insurance and those without insurance. The data collected were monthly and yearly hospital attendance from 2008 to 2017 for insured and non-insured patients grouped according to gender and age groups. Because the study was focused on use of National Health Insurance or without National Health Insurance, a list of ten years hospital attendance records was considered for the period 2008 – 2017. The research seeks to investigate whether the introduction of the National Health Insurance has increased attendance in the hospitals over Cash and Carry system. Chi-square tests and predictive modelling of the hospital attendance using Box-Jenkins's methodology of time series analysis were used to find out if there is a significant association between the users of health insurance and the cash and carry system in terms of their hospital attendance.

2.1. Chi-Square Test for Association

The test was performed to determine if there is any association between insurance status (that is health insurance and cash and carry patients) and gender in addition whether there is any association between hospital attendances for type of system of healthcare (health insurance and Cash and Carry systems) and years.

The null and alternative hypotheses are stated as follows:

Test for Association between Hospital Attendance and Gender

H_0: There is no association in attendance between gender and insurance status.

H_1: There is an association in attendance between gender and insurance status.

Test for Association between Hospital Attendance and Year

H_o: There is no association between hospital attendances for type of system of healthcare and years.

H_1: There is an association between hospital attendances for type of system of healthcare and years.

The chi-squared statistic for testing the null hypothesis H_0 has the test-statistic given by

$$x^2 = \sum \frac{(n_{ij}-\mu_{ij})^2}{\mu_{ij}} \tag{1}$$

where, n_{ij} = Observed value and μ_{ij} = expected value.

This statistic takes its minimum value of zero when all $n_{ij} = \mu_{ij}$. For a fixed sample size, greater differences in $n_{ij} - \mu_{ij}$ produces larger x^2 values and stronger evidence against H_o, with the probability of the level of significance of the test represented as a p$-value$. The x^2 statistic has approximately a chi-squared distribution and the chi-square approximation improves as μ_{ij} increases and also $\mu_{ij} \geq 5$ is usually sufficient for a decent approximation PSU (2018d) [5].

2.2. Time Series Analysis

It uses past behaviour of the variable in order to predict it future behaviour. Time series data consist of observations on a variable of interest collected in time order denoted $Y_1, Y_2, \ldots, Y_n$ where $t \in N$ such that $t = 1, 2, \ldots$ denote time steps, usually weekly, monthly, quarterly, yearly and etc. It is applicable when the number of variables of interest is univariate or multivariate. It is possible in time series one will have either an increase or decrease in trend and when there is no such pattern, it means the time series is stationary. The nature of the variable of interest is continuous time series and discrete time series (observations are made only at specific times). The components of time series are the trend, seasonal variation, cyclical variation and irregular variation. The Australian Bureau of Statistics (ABS, 2008), [6] explained a trend is giving by a continuous long term variable or movement of the points over a period of time. A trend that is time dependent is called a random walk or stochastic variable. Seasonality occurs when the time series exhibit regular fluctuations each year about the same time with some contributing factors as weather conditions and festivities. Two ways to put the four components together in Time Series Models are:

i. Additive Model
ii. Multiplicative Model

Additive Model:

$$Y_t = TR_t + S_t + C_t + I_t \tag{2}$$

Multiplicative Model:

$$Y_t = TR_t \times S_t \times C_t \times I_t \tag{3}$$

PSU (2018a)

Where:

Y_t = Value of time series at time t
TR_t = Value of trend at time t
S_t = Value of seasonal variation at time t
C_t = Value of cyclical variation at time t
I_t = Value of irregular variation at time t

White noise process also referred to as purely random process is defined as a sequence $\{e_t\}^{\infty}$ of uncorrelated random variable with zero mean and variance equal to a constant σ^2. In a random walk, a current value of the random variable x, is a combination of past value x_{t-1} and an error (WN). Smoothing techniques "smooth out" random fluctuations caused by the irregular component of the series which is particularly suitable for stationary series. These models include moving averages, single and double exponential smoothing, auto-regressive integrated moving average (ARIMA) and others. Also, we find seasonal effect so as to remove the seasonal effect from the series and the process is called deseasonalization. Stationary series exist in time series and it assumptions are constant mean, constant variance, and constant autocorrelation structure.

2.2.1. Moving Average (MA) Models

MA models provide predictions of Y_t based on a linear combination of past forecast errors. It is one of the smoothing techniques.

Thus the moving average operator is defined as:

$$\theta\ (B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q \tag{4}$$

2.2.2. The Autoregressive Integrated Moving Average Model (ARIMA)

Differencing is done in time series to a non-stationary dataset, having variation in the mean to remove such variation, the remaining series is called an integrated time series. The name an integrated model since the stationary model which is fitted to the differenced data has to be summed or integrated to provide a model for the non-stationary data. Notational, all AR (p) and MA (q) models can be represented as ARIMA (1, 0, 0) meaning no differencing and no MA part. The general model is ARIMA (p,d,q) where p is the order of the AR part, d is the degree of differencing and q is the order of the MA part. The ARIMA process according to qmul (2018a), [7] can be written as

$$Y_t = V^d Y_t = (1 - B)^d Y_t \tag{5}$$

The general ARIMA process is of the form:

$$Y_t = \sum_{i=1}^{p} \alpha_i Y_t - i + \sum_{i=1}^{q} \theta_i e_t - i + \mu + et \tag{6}$$

Box Jenkins methodology uses moving averages and autoregressive approaches (Box, Jenkins and Reinsel, 1994) [8]. However, as formulated by Box and Jenkins (1976) [9] is the development of autoregressive integrated moving average (ARIMA) models to deal with forecasting and time correlated modeling. The general behavior of the ACF and PACF for ARMA/ARIMA models is summarized according to qmul (2018b) [10] as:

Table 1. *Behavior of ACF and PACF for ARMA models.*

	AR (p)	MA (q)	AARMA (p, q), p > 0, and q
ACF	Tails off	Cuts off after lag q	Tails off
PACF	Cuts off after lag p	Tails off	Tails off

2.2.3 Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

Measuring the association between current and past time series values are known as ACF and PACF. Autocorrelation function (ACF), measures linear dependence in time series, k time periods apart. Partial autocorrelation function (PACF), measures linear dependence in time series k accounting for the values of the intervals as well as points of time as a function at lag t.

2.2.4. Seasonal ARIMA (SARIMA) Model

Seasonality is one of the usual patterns of changes over specified time period say t where it explains the number of time periods until the pattern repeats again. In a seasonal ARIMA model, seasonal AR and MA terms predict x_t using data values and errors at times with lags that are multiples of S (the span of the seasonality). We perform differencing in time series to examine differenced data when we have seasonality. Seasonality usually causes the series to be non-stationary because the average values at some particular times within the seasonal span (e.g. months) may be different than the average values at other times. The seasonal differencing is defined as a difference between a value and a value with lag that is a multiple of *S*. With *S*= 12, which may occur with monthly data, a seasonal difference is $(1\text{-}B^{12})x_t{=}x_t\text{-}x_{t-12}$. The differences (from the previous year) may be about the same for each age group or month of the year obtaining a stationary series. With $S = 4$, which may occur with quarterly data, a seasonal difference is $(1\text{-}B^4)x_t{=}x_t\text{-}x_{t-4}$. Seasonal differencing removes seasonal trend and can also get rid of a seasonal random walk type of non-stationarity. If trend is present in the data, we may also need non-seasonal differencing. Often (not always) a first difference (non-seasonal) will "detrend" the data. That is, we use $(1\text{-}B)x_t{=}x_t\text{-}x_{t-1}$ in the presence of trend. When both trend and seasonality are present, we may need to apply both a non-seasonal first difference and a seasonal difference. ARIMA (*p, d, q*) × (*P, D, Q*)$_S$, where p = non-seasonal AR order, d = non-seasonal differencing, q = non-seasonal MA order, P = seasonal AR order, D = seasonal differencing, Q = seasonal MA order, and S = time span of repeating seasonal pattern [11, 12].

2.2.5. Ljung-Box Statistic

Ljung-Box statistic (also called Box-Pierce statistic) is a diagnostic tool applied to examine residuals from a time series model in order to observe if all underlying population autocorrelations for the errors may be 0 (up to a specified point). It is purely based on the autocorrelation plot. Instead of testing at each distinct lag, it tests rather the overall randomness based on the number of lags. The residuals are assumed to be "white noise," meaning they are identically, independently distributed from each other. The ACF for residuals is that all autocorrelations are 0. This means that Q (m) should be 0 for any lag m. A significant Q (m) for residuals indicates a possible problem with the model. Q (m) measures accumulated autocorrelation up to lag m:

$$Q(m) = n(n+2)\sum_{j=1}^{m}\frac{r_j^2}{n-j} \tag{7}$$

where n is the sample size after any differencing operation, and the test statistic follows the chi-square distribution with degrees of freedom $(df) = m - p$. The p-value is determined as the probability past Q (m) in the significant distribution. A small p-value (say p-value < 0.05) indicates the possibility of non-zero autocorrelation within the first m lags PSU (2018c) [11, 12].

3. Data Analysis and Results

Table 2. *Chi-square test for association of hospital attendance with gender.*

	Insured_1	Non-Insured_2	All
Male	337123 (343893)	63660 (56890)	400783
Female	508695 (501925)	76263 (83033)	584958
All	845818	139923	985741

From the output, since the $x^2 = 1582.238$ with a $p-value = 0.00$ is less than the alpha value of 0.05, we reject the null hypothesis. Therefore we conclude that the hospital attendances for insured and non- insured patients have dependency on gender.

Table 3. *Test for Association between Hospital Attendance and Year.*

Year	Insured_1	Non-Insured_2	All
2008	58393 (86692)	42640 (14341)	101033
2009	79735 (100709)	37634 (16660)	117369
2010	76437 (88687)	26921 (14671)	103358
2011	71747 (71726)	11844 (11865)	83591
2012	81673 (74767)	5463 (12369)	87136
2013	86480 (75688)	1729 (12521)	88209
2014	92646 (82068)	2998 (13576)	95644
2015	95470 (83778)	2167 (13859)	97637
2016	101957 (89797)	2695 (14855)	104652
2017	101280 (91908)	5832 (15204)	107112
All	845818	139923	985741

In brackets are the expected frequencies:
Pearson Chi-Square = 162538.620, DF = 9, P-Value = 0.000
Likelihood Ratio Chi-Square = 158041.033, DF = 9, P-Value = 0.000

The output above in Table 3 gives a p-value of 0.000 with degrees of freedom of 9 which is less than the alpha vale of 0.05 indicates that the test is statistically significant. We reject the null hypothesis hence there is evidence of dependence in the hospital attendance between insured as well as non-insured patients and the years.

Test for Stationarity of Insured Data

In checking for the stationarity of the dataset before using it to forecast, KPSS test was employed.

KPSS Test.

(H_0): Data set is stationary
(H_1): Data set is not stationary.
The test results are presented in Table 4:

Table 4. *A KPSS test for level stationarity for insured patients.*

Data	KPSS level	Truncation lag parameter	P-value	Alpha value
Raw Data	0.35626	2	0.09601	0.05

Using KPSS test for the raw insured data, since the p-value ≈ 0.10, greater than α = 0.05, we fail to reject the null hypothesis H_0. Hence, we conclude that the series of the raw insured data is level stationary, therefore needs no differencing.

Parameter Estimation and Model Validation for Insured Data.

Table 6 indicates the selected ARIMA models with their AIC values. Figure 2 captures the model diagnostics.

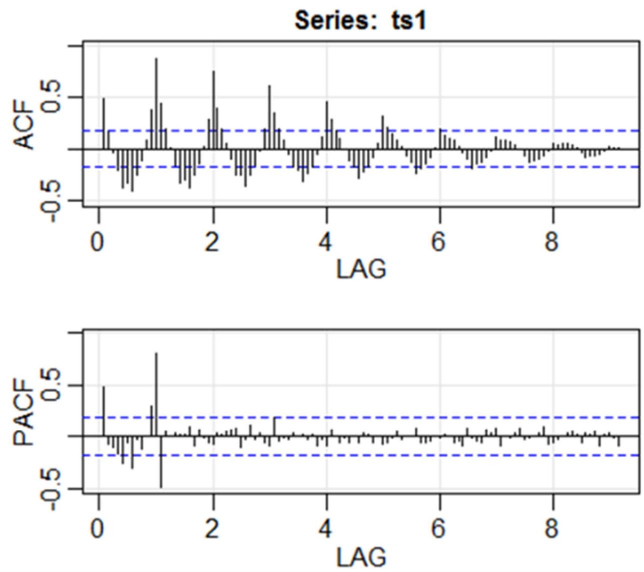

Figure 1. *Autocorrelation and partial autocorrelation functions of insured data.*

The autocorrelation function (ACF) and partial autocorrelation function (PACF) as shown in Figure 1. The graphs suggest an AR process with order 1. Candidate models were obtained using the minimum AIC criteria to select more adequate model. To confirm the appropriate model, seasonal ARIMA model was obtained.

Table 5. *ARIMA (1,0,0) $(0,1,0)_{12}$ model results.*

Model	AIC Value	S.E_ar1
ARIMA (1,0,0) $(0,1,0)_{12}$	15.66537	0.0842

This model was used to modify the AR1 process chosen. The best SARIMA (1, 0, 0) $(0, 1, 0)_{12}$ model with least AIC value of 15.66537 was fitted using the SARIMA function.

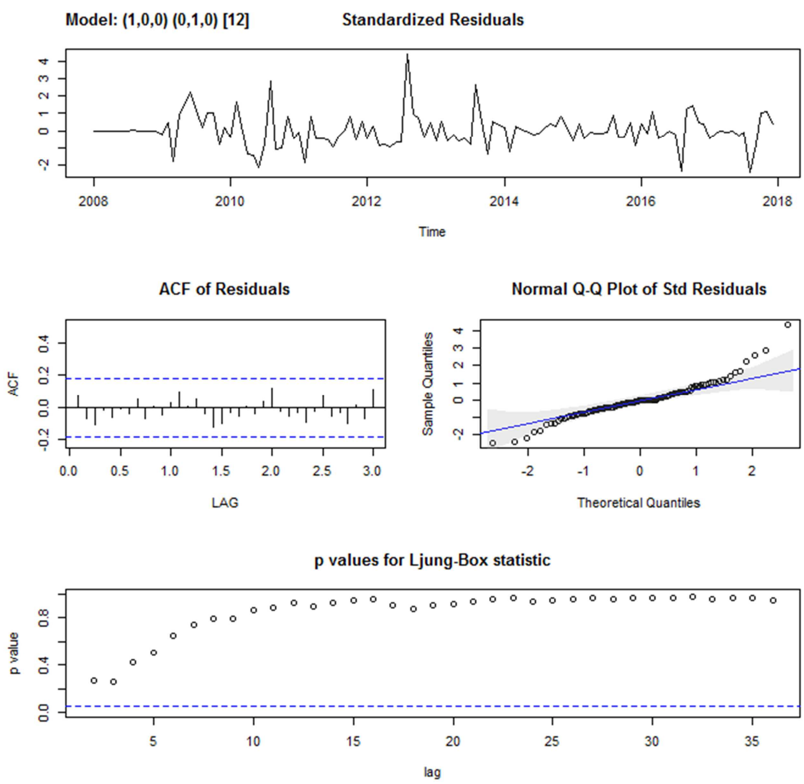

Figure 2. *Model diagnostics of insured data by Ljung-Box test showing the residuals are uncorrelated (ACF plot), independent and normally distributed by the QQ-plot.*

The residual diagnostic test in Figure 2 is performed using the Ljung-Box test for further confirmation of the selected model.

Table 6. *Summary of models for insured data.*

Model	AIC Value	S.E_ar1	S.E_ar2	S.E_ma1	S.E_ma2
ARIMA (1,0,0) $(0,1,0)_{12}$	15.66537	0.0842			
ARIMA (1,0,1) $(0,1,0)_{12}$	15.66711	0.1634		0.1613	
ARIMA (1,0,2) $(0,1,0)_{12}$	15.67878	0.2421		0.2475	0.1195
ARIMA (2,0,0) $(0,1,0)_{12}$	15.66835	0.0949	0.095		
ARIMA (0,0,1) $(0,1,0)_{12}$	15.67968			0.0723	
ARIMA (0,0,2) $(0,1,0)_{12}$	15.66958			0.0958	0.0940

Table 6 presents summary of the possible models together with their AIC values.

Test for Stationarity of Non-Insured Data

KPSS Stationarity test is performed.

KPSS Test

(H_0): Data set is stationary

(H_1): Data set is not stationary.

The test results are presented in Table 7:

Table 7. *A KPSS test for level stationarity for non-insured patients.*

Data	KPSS level	Truncation lag parameter	P-value	Alpha value
Before differencing	2.616	2	0.01	0.05
After differencing	0.045942	2	0.1	0.05

With the raw insured data, since the p-value=0.01 is less than α=0.05, we reject the null hypothesis and conclude that the series of the raw non-insured data is not level stationary. For the differenced insured data, since the p-value=0.1 is greater than α=0.05, we fail to reject the null hypothesis and therefore conclude that the series of the differenced insurance data is level stationary. The differenced series can now be used for forecasting.

Parameter Estimation and Model Validation for Non-Insured Data

Table 9 indicates the selected ARIMA models and corresponding AIC values. Figure 4 captures the model diagnostics.

The autocorrelation function (ACF) and partial autocorrelation function (PACF) as shown in Figure 3 suggest an AR process with order 1. Candidate models were obtained using the minimum AIC criteria to select more adequate model. The ACF and PACF plots suggest that, the series is a mixture of AR and MA process. The AIC of the candidate model shows that AR1MA is a better model.

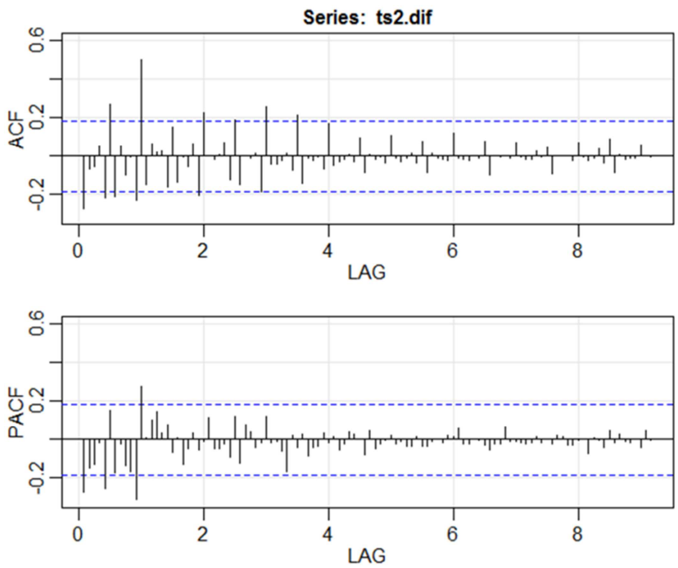

Figure 3. *Autocorrelation and partial autocorrelation functions of non-insured differenced data.*

Table 8. *ARIMA (1,1,1) (2,0,1)$_{12}$ model results.*

MODEL	AIC Value	S.E ar1	S.E ma1	S.E ma2	S.E sar1	S.E sar2	S.E smar1
ARIMA(1,1,1) (2,0,1)$_{12}$	13.94181	0.1034	0.0389		0.2479	0.2262	0.2264

We fit the AR1MA (1, 1, 1) (2, 0, 1)$_{12}$ model with the seasonality components and the least AIC value of 13.94181, which appears to be much better model is obtained.

Table 9. *Summary of models for non-insured data.*

MODEL	AIC Value	S.E ar1	S.E ma1	S.E ma2	S.E sar1	S.E sar2	S.E smar1
ARIMA(1,1,0) (2,0,1)$_{12}$	14.14381	0.0920			0.2064	0.1972	
ARIMA(1,1,1) (2,0,1)$_{12}$	13.94181	0.1034	0.0389		0.2479	0.2262	0.2264
ARIMA(0,1,1) (2,0,1)$_{12}$	14.00311		0.1516		0.2691	0.2400	0.2464
ARIMA(0,1,2) (2,0,1)$_{12}$	13.94305		0.0898	0.0904	0.2608	0.2363	0.240

The summary of other candidate models are given in Table 9, from which the best model is SARIMA (1,1,1) (2,0,1)$_{12}$ was chosen with least AIC value of 13.94181.

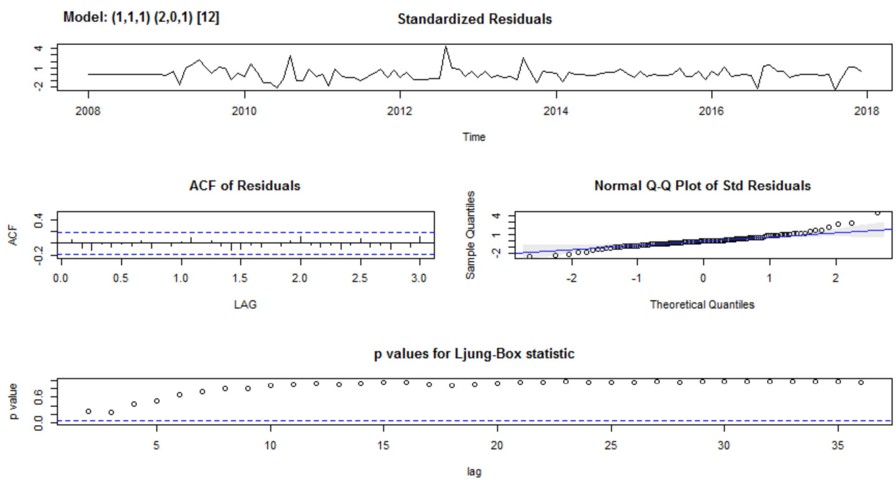

Figure 4. *Model diagnostics of non-insured data by Ljung-Box test showing the residuals are uncorrelated (ACF plot), independent and normally distributed by the QQ-plot.*

The residual diagnostic test as shown in Figure 4 is performed using the Ljung-Box test for further confirmation of the selected model.

4. Discussions

Table 10. *Forecasted values of insured hospital attendance.*

Age Group	0-28 days	1-11 month	1-4 Yrs.	5-9 Yrs.	10-14 Yrs.	15-17 Yrs.	18-19 Yrs.	20-34 Yrs.	35-49 Yrs.	50-59 Yrs.	60-69 Yrs.	70+ Yrs
Forecast 2018	2821	3921	7548	4019	2969	2474	1970	19631	16245	16095	15680	14004
Forecast 2019	3226	4326	7953	4424	3374	28799	2376	200361	16650	16500	16085	14409

Table 11. *Forecasted values for non-insured patients.*

Age Group	0-28 days	1-11 month	1-4 Yrs.	5-9 Yrs.	10-14 Yrs.	15-17 Yrs.	18-19 Yrs.	20-34 Yrs.	35-49 Yrs.	50-59 Yrs.	60-69 Yrs.	70+ Yrs.
Forecast 2018	81	161	235	232	260	155	109	1973	1318	816	166	85
Forecast 2019	130	196	237	227	232	192	164	1326	923	588	177	118

It can be seen from Table 10 that attendance for insured patients on the various age groups over two years period exhibited an increasing trend. This trend shows how health insurance scheme mode of attending hospital will continue to be used by patients seeking healthcare. From Table 11, it can be observed that the specific age groups of 0-28 days to 5-9 years, 15-17yrs.to 18-19yrs. and 60-69yrs. to 70+yrs have all experienced an increase over the two years period being forecasted for non-insurance. This suggests hospital attendance for these age groups will continue using the cash and carry system of paying hospital bills for the next two years. It can be observed that attendance for the various age groups on the forecasted two years period have experienced an increase over the last year under review which is 2017. Even though the increment is not a fast one, it recorded a gradual increase for the forecasted years.

Table 12. *2018 Forecasted Values for Insured Age Group Hospital Attendance Compared with Actual 2017 Attendance Review.*

Age Group	0-28 days	1-11 month	1-4Yrs.	5-9 Yrs.	10-14 Yrs.	15-17 Yrs.
Actual 2017	1766	3208	6997	3545	2531	2053
Forecast 2018	2820.982	3920.967	7547.956	4019.213	2968.860	2473.640

Table 12. *Continued.*

Age Group	18-19 Yrs.	20-34 Yrs.	35-49 Yrs.	50-59 Yrs.	60-69 Yrs.	70 Yrs. & Above
Actual 2017	1558	19222	15838	15689	15274	13599
Forecast 2018	1970.483	19630.619	16244.789	16094.922	15679.511	14004.317

Table 13. *2018 Forecasted Values for Non-Insured Age Group Hospital Attendance Compared with Actual 2017 Attendance Review.*

Age Group	0-28 days	1-11 month	1-4 Yrs.	5-9 Yrs.	10-14 Yrs.	15-17 Yrs.
Actual 2017	29	89	151	140	161	139
Forecast 2018	80.84241	161.07327	234.91726	232.21231	260.00504	155.30869

Table 13. *Continued.*

Age Group	18-19 Yrs.	20-34 Yrs.	35-49 Yrs.	50-59 Yrs.	60-69 Yrs.	70 Yrs. & Above
Actual 2017	116	2201	1520	929	221	136
Forecast 2018	108.56674	1972.86489	1318.01079	815.51885	166.34544	85.25510

From Table 12, one can observe that the values for the forecast age groups are greater than the actual values across the various age groups. This means that patients using health insurance will be increasing for the year under forecast as compared to the number of attendance of the year under review. Continues use of the insurance system will see an increase in attendance for 20-34 years in the coming year recording the age group that has the highest number of hospital visits.

From Table 13 there is an increase in the forecasted values for age groups 0-28 days to 15-17 years under 2018 with the hospital attendance of patients using cash and carry system as compared to the actual hospital attendance for 2017. Meaning this categorical of age group will continue to use Cash and Carry System in seeking healthcare more than other categories under the age limits specified. From 18-19 years, the forecasted values incline to decrease to the ending of the age group 70 Yrs. & above. Though age group 20-34 years recorded the highest forecasted value, it also reduced compared to the actual value of attendance in the year 2017. Comparing the forecasted with the actual values of attendance, we can observe that there are changes in the age groups attendance recording an increase and decrease trend in the forecast values. This trend indicate patients using cash and carry system will increase with specific age groups (0-28 days to 15-17 6years) using the system and reduce with age groups (18-19 years to 70 Yrs. & Above) for attendance in year 2018.

5. Conclusions

The study applied time series methodology to hospital attendance data with the aim of analysing the Cash and Carry and the Insurance systems of payment of hospital bills at Cape Coast Teaching hospital. The study also determined the association between the two systems using Chi-square tests. The study formulated tentative models for the two systems of paying hospital bills with selected models for insured and non-insured data. These models were selected as a result of their lowest AIC values. The study used the best model fit to forecast for 2018 and 2019.

There is an established significant association of hospital attendance for patients using both systems (health insurance and cash and carry) with gender and years confirmed by the Chi-square tests. The number of health insurance user's differs across levels of cash and carry patients in years with hospital attendance seeking healthcare. Hence, the use of the health insurance scheme to seeking medical care has increased hospital attendance with time while patients using cash and carry system continues to increasing attendance particularly for the age groups, 1 day throughout to 17 years.

6. Recommendations

Education should be given to the general public about the importance of health insurance, it registration and operations especially age group 0-28days to 15-17 years because they seem to continue the use of Cash and Carry System in seeking healthcare regardless of the introduction of NHIS. The government should promote the continuation of the use of the national health insurance scheme to all categories of patients. There should be an expansion of the existing health insurance registration centres and establishing new centres especially in the rural communities since the hospital receives mostly referral.

Author Contributions

Bridget Sena Borbor is the main author who conceived the idea for research, collected the data, performed the analysis and interpreted the results. She also reviewed the manuscript at all stages.

Bosson-Amedenu Senyefia reviewed related literature for the paper and did the write up for the introduction. He did review the manuscript at the early stage and fine-tuned the write-up of the analysis.

Daniel Gbormittah further reviewed the manuscript for it publication content before submission and made suggestions on the conclusion.

Conflict of Interest Statement

This research paper has not been submitted elsewhere to be published.

Implication for Further Research

Future research can concentrate on children to find reasons why categories of children continue using cash and carry system. For more robust results future research can use data spanning more than 10 years.

Limitation of the Study

Only one teaching hospital was incorporated in the research.

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Biography

Bridget Sena Borbor works as a Public Servant. She is a PhD in Mathematics candidate at the University of Mines and Technology. She holds research Master's degree in Applied Statistics from the Kwame Nkrumah University of Science and Technology, a Bachelor of Science (BSc.) degree in Statistics from the University of Cape Coast-Ghana and a Higher National Diploma in Statistics from the Cape Coast Polytechnic. Her research interests include Time Series Analysis, Applied Statistics, Biostatistics, Population and Development Statistics.

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Daniel Gbormittah currently works at Komenda College of Education in Komenda, Ghana as a Mathematics tutor in the Department of Mathematics and ICT education. He also doubles as the deputy quality assurance officer of the College. He holds Master of Philosophy degree in Mathematics and B.Ed. degree in Mathematics all from University of Cape Coast. He has worked as a Senior High School Mathematics teacher at Wesley Girls High in Cape Coast, Ghana from 2013 to 2018. His research interest includes understanding how learners learn mathematics linked with their sociocultural practices and an ethnomathematics educator.