

Modeling Volatility Clustering in Daily Demand for Emergency Healthcare Services in The University of Cape Coast Hospital, Ghana: A Longitudinal Study

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ABSTRACT

Introduction: Since early 2020, demand for emergency healthcare services in the University of Cape Coast hospital has become increasingly volatile. This phenomenon is a cause for concern because sudden and unexpected shifts in demand for emergency healthcare services can and have created expensive disruptions in operational activities even for very well-run and sophisticated emergency healthcare systems elsewhere. These phenomena of shifts in demand often create shocks in the system called *volatility clustering*. This is used as a crude measure of the risk of operations in the emergency healthcare industry for strategic planning, readiness, and swift response to demand for emergency healthcare services. Modeling these volatilities is crucial for prudent risk management practices such as proactively curtailing losses or liabilities, negative spillover effects, medicinal supply chain disruptions, and overall costs among key stakeholders. Despite its relevance, the knowledge of volatility density clustering in the demand for emergency healthcare in the hospital is complex and imprecise and the model(s) explaining it remains unknown. **Methods:** a longitudinal study was conducted by using high-frequency data of daily returns of the demand for emergency healthcare services in the hospital from January 2020 through June 2022. The Generalized Autoregressive Conditionally Heteroscedastic (GARCH)

models were deployed to analyze the data. *Eviews 10* statistical software package was used to process the data with statistical significance set at 5%. **Results:** this unbiased research study revealed a current daily average admissions of 35 patients on an 11-bed capacity emergency ward and an overall emergency admission of 13,656 patients over the study period. The results showed that the daily returns of the demand for emergency healthcare in the hospital exhibited high and persistent volatility clustering with the observed R-squared LM-statistic = 20.15; $p < .001$, for the returns series and suggesting $GARCH(1, 1) = .001592 + .053825\hat{u}_{t-1}^2 + .927965\hat{\sigma}_{t-1}^2$ as the optimal model out of six explanatory candidate volatility models. By implication, the associated volatility with the current operational capacity is woefully inadequate. **Conclusion:** countermeasures and supporting tools need to be designed and developed by management to guarantee readiness for rapid response, monitor and minimize any undesirable outcomes, and ultimately maximize quality patient care and safety.

Keywords: Volatility Clustering, Modeling, GARCH, Daily Demand, Emergency Healthcare

INTRODUCTION

Background/Rationale

Volatility clustering is a common phenomenon in financial econometrics modeling literature where significant changes in the returns of asset prices cluster together. In other words, periods of turbulence are followed by periods of turbulence, and periods of tranquility are followed by periods of tranquility. Mandelbrot [1] was a pioneer in demonstrating the phenomenon of volatility clustering and popularized by other researchers such as Engle and Bollerslev [2, 3]. Hence, researchers in the emergency healthcare industry have recognized the relevance of econometric models and have proposed and applied these models in healthcare utilization [4, 5] and to address wide swings (volatility of variance) exhibited in the daily demand for emergency healthcare services in hospitals [6]. Studies have shown that there is a growing trend in the demand for emergency healthcare worldwide as a result of increased road traffic accidents, changing nature of primary health care, and increasing trends of epidemics and pandemics [7, 8, 9]. This has intensified risk and burnout with their attended repercussions for both managers and professionals of the emergency healthcare industry worldwide. In Ghana, as in many developing countries, the rising cases of road traffic accidents, substance abuse, violence, domestic accidents, medical emergencies, surgical emergencies, epidemics, etc. often overwhelmed the accident and emergency departments of major healthcare centers [10, 11, 12]. The daily arrival of these cases at the accident and emergency centers of hospitals is seemingly random and is seriously characterized by wide swings and their associated risks and this phenomenon poses a major challenge to emergency healthcare providers.

Significant strides have been made in the emergency healthcare industry in Ghana in recent years and the field has been recognized and supported by the Ghana College of Physicians and Surgeons (GCPS) with an increasing commitment of resources for infrastructure and human resource development [12]. As part of the strategies for improving the quality of emergency healthcare services delivery, the appropriateness, effectiveness, relevance, and efficient management of the patient flow in hospital emergency departments have become a key focus in the emergency healthcare industry at national and international levels. Thus far, this is to enhance the quality-of-care delivery and avoid the risk of the effects of the wide swings

(volatility of variance) in patients' arrivals at emergency healthcare service centers which in turn generate unexpected overcrowding and consequently increased waiting time [6]. These incidences are detrimental to the lives of injured and vulnerable patients on arrival; these phenomena directly lead to 5 million deaths every year, accounting for 9% of all deaths worldwide [11].

While knowledge of the pattern and volatility of variance of daily demand for emergency healthcare services at the hospitals is essential to plan health interventions and enable healthcare service providers to take appropriate mitigating actions to minimize risks and manage the demand for emergency healthcare services, unfortunately, these are not thoroughly investigated in Ghana [11, 13]. Therefore, experts feel it expedient to not only accurately estimate and forecast the daily demand for emergency healthcare services [14] but modeling the volatility of daily demand for emergency healthcare services has considerable implications for resource planning and strategic allocation in emergency healthcare centers. Representative studies in Ghana and elsewhere have investigated and estimated mean autoregressive integrated moving average (ARIMA) models for the daily demand for emergency healthcare services in accident and emergency departments in hospitals [14, 15, 16]. However, the literature has not gone further to model the volatility of the daily demand for emergency healthcare services; the benefits of which cannot be overestimated. Hence, using the daily demand for emergency healthcare services at the accident and emergency department of the University of Cape Coast Hospital in Ghana; the paper specifically outlined a number of objectives intended to assess volatility clustering in the daily demand for emergency healthcare services in the hospital.

Objectives

This paper intended to

- (1) examine ARCH effects
- (2) estimate ARCH or GARCH model(s), and
- (3) forecast ARCH or GARCH volatility.

Study Hypothesis

Null Hypothesis: There are no existing ARCH or GARCH effects

Alternative Hypothesis: There are existing ARCH or GARCH effects

METHODS

Study Design

The research study design adopted was longitudinal which features large series of observations made on the same variable consecutively over time. The study gathered data to systematically examine and describe the phenomenon of volatility clustering in the returns of daily demand for emergency healthcare services at the University of Cape Coast Hospital, Ghana. The data was processed using *EViews 10* statistical software package. Statistical significance was set at 5%.

Study Setting

The University of Cape Coast is a public collegiate university located in the historic town of Cape Coast in the central region of Ghana. The university is one of the rare sea-front universities in

the world and sits on a hill above sea level overlooking the Gulf of Guinea to the south. The university hospital which is located on the south campus of the University takes charge of the health needs of the University community and its environs. The hospital's emergency healthcare department (12 beds) is equipped with specially trained staff and provides services for its clients at all times. Daily demand for emergency healthcare data was collected over the period of January 2020 through June 2022 for the investigation.

Study Variable

In this univariate time series modeling, only one variable was required for the modeling of the volatility of variance of the time series variable. The variable of interest employed for investigation in this study was the daily demand for emergency healthcare in the University of Cape Coast Hospital, Ghana for the period of January 2020 through June 2022.

Data Sources

The study employed daily demand for emergency healthcare at the accident and emergency department of the University of Cape Coast Hospital from January 2020 through June 2022. The data was collected from the accident and emergency department register with expressed permission from management. This task was accomplished by simply taking the total frequencies of daily patient arrivals for emergency healthcare.

Potential Sources of Bias

In ARCH and Generalized ARCH models using low-frequency data such as quarterly or annually and also using a small sample, size data have the tendency of altering the true research results. Hence, to maintain objectivity and avoid these potential sources of bias, calculated efforts were made to collect high-frequency data (daily demand) over a 30-month period (for larger sample size). Similarly, the problem of missing data was unavoidable, and its existence had the potential of reducing the power of the investigation. However, the statistical technique of simple moving average of a rolling window 5 was used to intervene to curb the phenomenon.

Sample Size

Empirical research [17] has suggested a minimum sample size of 100 time-series observations or a period of one hundred days of consecutive daily frequency data when dealing with regression models for meaningful results. However, ARCH and GARCH models are inevitably more data-intensive than those based on simple linear regressions and work better when the data are sampled daily rather than at a lower frequency. Hence, the study employed daily frequency data of the demand for emergency healthcare services in the hospital for a period of two and half years and obtained a total of 912 days of time-series observations for the analysis.

Statistical Methods

The classical linear regression model (CLRM) assumes that the error of a formulated regression model is homoscedastic. However, it is empirically unlikely to have constant variance over time (all the time). This implies that the error term may exhibit heterogeneity (time-varying variance) which results in unreliable standard error estimates in the model. Hence, the need to design models that do not assume homogeneity of variance, and these models include ARCH and Generalized ARCH (GARCH) models.

ARCH Models:

In traditional time-series modeling, non-linear models do not assume homogeneity of variance and describe how the variance of the errors evolves. The Autoregressive Conditional Heteroscedasticity (ARCH) model popularized by Engle (1982) [2] models 'autocorrelation in volatility' by making the conditional variance (h_t) of the error term a function of its immediate past value of the squared error. This is mathematically expressed as

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 \quad (1)$$

Model (1) is referred to as ARCH (1). Where the error variance depends on q lags of squared errors, this is referred to as the ARCH (q) model expressed as the model (2) below on condition that $\alpha_0 \geq 0$, $\alpha_i \geq 0 \forall i = 0, 1, 2, \dots, q$. and $0 \leq \sum_{i=1}^q \alpha_i < 1$.

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_q u_{t-q}^2 \quad (2)$$

However, the ARCH models have rarely been used in the empirical literature for the past decade as a result of some challenges that come with them. Hence, Generalized ARCH models are promulgated for usage and are widely used in practice.

Generalized ARCH (GARCH) Models:

The Generalized ARCH model was independently developed by Bollerslev and Taylor [2, 18]. They allowed the conditional variance (h_t) to be dependent upon previous own lags. This is expressed mathematically as

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

Model (3) is referred to as GARCH (1, 1) and can generally be extended to GARCH (p, q) where the current conditional variance is parameterized to depend upon q lags of the squared error and also p lags of the conditional variance as expressed in model (4).

$$h_t = \sum_{i=1}^q \alpha_i u_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (4)$$

Testing for GARCH Effects:

Before estimating a GARCH-type model, it is essential that the presence of ARCH effects is tested for in the model to ensure that this class of models are appropriate for the data. Therefore, the mean regression equation for the data was postulated and the error extracted, squared, and regressed on q own lags for the ARCH (q) effects. Algebraically, this is expressed as

$$\hat{u}_t^2 = \gamma_0 + \gamma_1 \hat{u}_{t-1}^2 + \gamma_2 \hat{u}_{t-2}^2 + \dots + \gamma_q \hat{u}_{t-q}^2 + \varepsilon_t \quad (5)$$

In model (5) the square of the estimated error is regressed over its own q lags and ε_t is an error term of the model. The test statistic follows a chi-squared distribution of $\chi^2(q)$. The null and alternative hypotheses include;

$$H_0: \gamma_1 = \gamma_2 = \dots = \gamma_q = 0, \quad H_1: \gamma_1 \neq \gamma_q \neq 0$$

The null hypothesis (H_0) is rejected if the calculated test statistic (the number of observations multiplied by the coefficient of multiple correlation) is greater than the critical value from the χ^2 -distribution, otherwise it cannot be rejected. Its rejection indicates the presence of ARCH effects.

Estimating GARCH Effects:

The family of GARCH models requires *maximum likelihood techniques* for estimation and not ordinary least squares (OLS) since they are non-linear models. Essentially, the method was executed by finding the appropriate equations for the mean and the variance of the daily demand for emergency healthcare services time-series variable. The log-likelihood function (*LLF*) was specified to maximize under a normality assumption for the disturbances. Models 6-8 demonstrated the estimation procedure mathematically. The statistical software package maximized the function and generated parameter values that maximized the *LLF* and constructed their standard errors.

$$y_t = \mu + \phi y_{t-1} + u_t, \quad u_t \sim N(0, \sigma_t^2) \quad (6)$$

$$h_t = \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (7)$$

$$L = -\frac{T}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^T \log(\sigma_t^2) - \frac{1}{2} \sum_{t=1}^T (y_t - \mu - \phi y_{t-1})^2 / \sigma_t^2 \quad (8)$$

Forecasting GARCH Volatility:

Forecast was made possible using *EViews 10* software package. The GARCH volatility forecast was obtained by using only a sub-sample of existing or actual data for model estimation, and then subsequently forecast the future volatility of the daily demand for emergency healthcare services in the hospital.

Model Selection:

In time-series analysis, there is no such as a perfect model. Nevertheless, the main challenge is to select a suitable model from a set of candidate models that will characterize the underlying data set. Hence, model selection criteria provide an easy avenue to examining whether an estimated model offers an optimal balance between goodness-of-fit and parsimony. The three most commonly used model selection criteria in the literature are Akaike Information Criterion (AIC), the Schwarz's Bayesian Information Criterion (SBIC), and the Hannan-Quinn criterion (HQIC). The model with the lowest AIC, SBIC, or HQIC value is the best candidate model for selection. Algebraically, these are expressed, respectively, as equations 9-11 with (9) as the chosen information criterion for this study.

$$AIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \quad (9)$$

$$SBIC = \ln(\hat{\sigma}^2) + \frac{k}{T} \ln T \quad (10)$$

$$HQIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \ln(\ln T) \quad (11)$$

Where $\hat{\sigma}^2$ is the residual variance, k is the total number of parameters estimated and T is the grand sample size of the investigation.

Addressing Missing Data:

In the real-world data is often not complete and usually contain missing values. This phenomenon was not different in the University Hospital Emergency Department register. There was a total of 42 missing time-series observations in the collected data due to staff failure in recording emergency cases in some specific dates in the accident and emergency register. This problem was dully addressed using the statistical technique such as Simple Moving Average of a rolling window 5 to complete the time-series data set for the analysis. Simple Moving Average of using a rolling window 5 means that the average of the immediate five previous values is taking to represent the missing observation or value.

RESULTS

Descriptive Analysis

This section presented the descriptive analysis of the daily demand for emergency healthcare services series in the University of Cape Coast hospital over the period of January 2020 through June 2022.

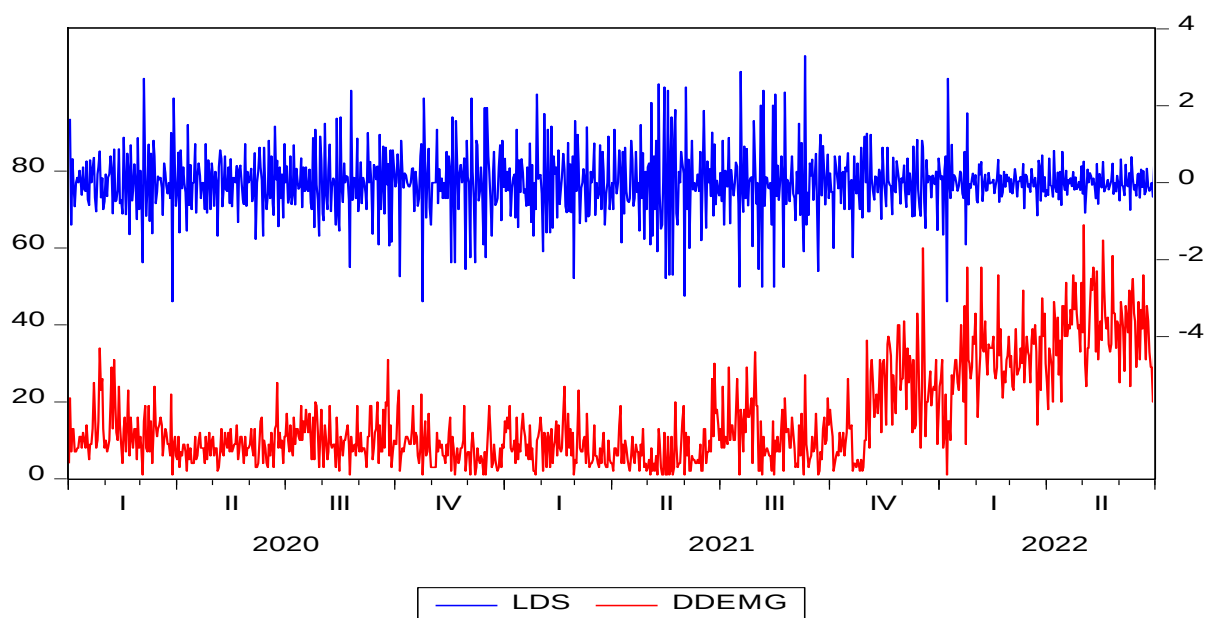


Figure 1: A graphical display of the returns (blue) and actuals (Red) of the daily demand for emergency healthcare

From figure 1 it can be seen that the evolution of the daily demand for emergency healthcare services in the (red graph) hospital was non-stationary and had a positive trend. The returns series graph (blue) of the evolution demonstrated periods of shocks and periods of calmness throughout the study period. The phenomenon of volatility clustering was discernible (blue graph) throughout the whole period of study as large changes tended to be followed by large changes, of either sign (+/-), and small changes tended to be followed by small changes. Volatility was relatively calm before the end and the beginning of the 1st and 2nd quarters of 2020. Thereafter, periods of calmness were mixed with turbulences through to the end of the

1st quarter of 2021. However, middle of 2nd quarter and 3rd quarter suffered high volatility with most of the 4th quarter experiencing relatively calmness. Volatility surged again in the ending part of the 4th quarter of 2021 and the beginning of the 1st quarter of 2022. There was relatively calmness for the most part of the 1st quarter and for the entirety of the 2nd quarter of 2022. Mean reversion was also evident.

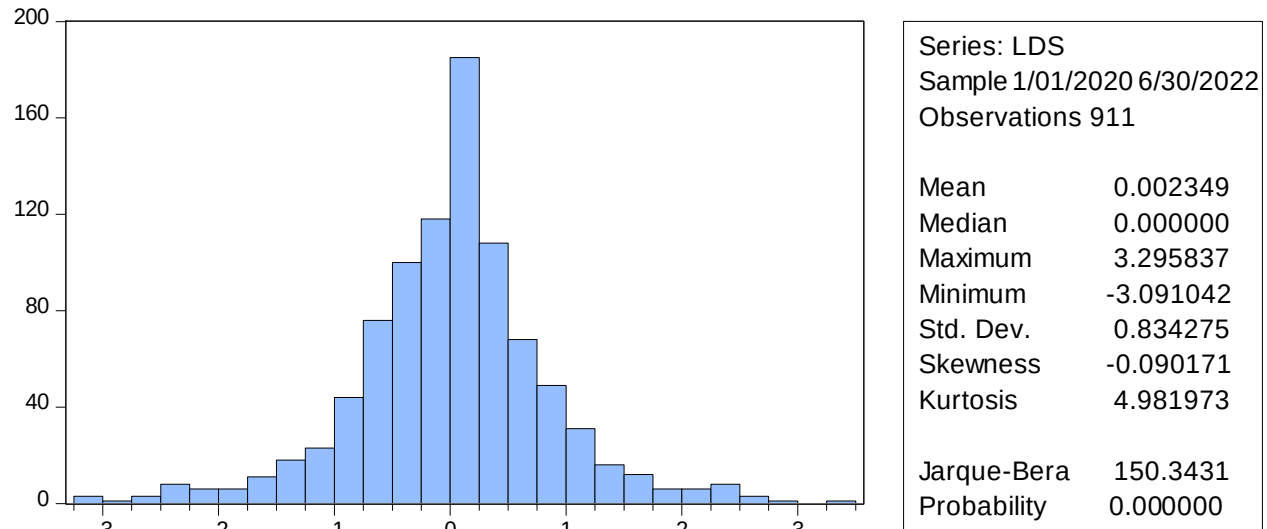


Figure 2: Histogram plot of the return's series of daily demand for emergency healthcare services

Figure 2 indicated the distribution of fatter tails than the usual normal distribution (leptokurtic). Hence, GARCH models are excellent in replicating such fatter tails as seen in this distribution compared to the ARCH counterpart models. Table 1 presents some descriptive statistics on the daily and quarterly demand for emergency healthcare services in the hospital for the study period.

Table 1: some descriptive statistics on daily and quarterly emergency healthcare service demand

Year/Quarter	Q1	Q2	Q3	Q4	Total	Quarterly demand		Daily demand		Professional attendants		Beds
						Mean	SD	Mean	SD	MD	RN	
2020	1082	747	999	721	3549	887	180	10	2	4	10	11
2021	801	575	740	1695	3811	953	503	12	6	4	9	11
2022	2715	3581	-	-	6296	3148	612	35	7	4	7	11
Total					13656							11

* Q1-Q4 = quarters of year, MD = assigned medical doctors, RN = assigned registered nurses, SD = standard deviation

From Table 1 number of available beds in the emergency ward were 11 with four (4) assigned medical doctors and supporting nurses as professional emergency care attendants throughout the study period. For the period of study there were a total of 13,656 emergency visits with the last two quarters experiencing over 6,000 emergency admissions and an average of 35 daily. The intense and wild volatile nature of the demand for emergency healthcare services in the

hospital for the study period is shown as a wild fluctuation in the daily as well as the quarterly standard deviation statistics.

Testing for ARCH Effects

The estimation of the GARCH models was preceded by testing for the presence of ARCH effects. The ARCH effects test is presented in Table 2.

Table 2: heteroscedasticity test: ARCH (1) test (dependent variable: RESID^2)

F-statistic	20.56277	Prob. F (1, 907)		0.0000
Obs*R-squared	20.15126	Prob. Chi-sq (1)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.451864	0.038445	11.75350	0.0000
Resid^2(-1)	0.148889	0.032834	4.534619	0.0000

From Table 2 the existence of ARCH effects is confirmed by the statistical significance of the observed R-squared p -value. The LM-statistic = 20.15; $p < 0.001$. The presence of ARCH effects paved the way for the estimation of ARCH or GARCH models in the residual of the series. Hence the null hypothesis that there are no existing ARCH/GARCH effects is rejected.

Estimation of the ARCH/GARCH in Mean Models and Selection Criteria

The presence of ARCH effects gave an indication for the estimation of GARCH models. Six estimated candidate models are presented in Table 3 for selection.

Table 3: estimated ARCH/GARCH candidate models for consideration and selection

Model	Coefficients	Sig. (+) Coeff	Adj. R-Sq	Log-likelihood	AIC
GARCH (1, 1)	3	2	0.233441	-923.2489	2.040107
GARCH (1, 2)	4	1	0.233136	-922.6316	2.040949
GARCH (2, 1)	4	2	0.232509	-921.1797	2.037758
GARCH (2, 2)	5	2	0.232820	-922.4097	2.042659
GARCH (3, 3)	7	4	0.232986	-914.8161	2.030365
GARCH (0, 3)	4	4	0.230341	-957.8408	2.118331

The empirical literature suggests that an optimal model should have the following characteristic to qualify for selection; (1) minimum number of parameters or coefficients-parsimony, (2) highest number of significant positive ARCH and GARCH coefficients, (3) highest adjusted R-squared, (4) highest log-likelihood ratio, and finally (5) minimum AIC or SBIC value. Also, the model must pass the *ARCH-LM test* and *no autocorrelation test* under model diagnostics. Table 3 indicated GARCH (1, 1) as having been successful in this criterion. An alternate model was ARCH (3).

Estimated Coefficients for Selected Models

Table 4: parameter estimation of models GARCH (1, 1) and ARCH (3)

Model	Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH (1,1)	Mean Equation				
	Constant	-0.012803	0.019028	-0.672877	0.5010
	LDS (-1)	-0.478049	0.028391	-16.83827	0.0000
	Variance Equation				
	Constant	0.001592	0.001145	1.389553	0.1647
	RESID (-1)^2	0.053825	0.010222	5.265603	0.0000
ARCH (3)	GARCH (-1)	0.927965	0.008244	112.5646	0.0000
	Mean Equation				
	Constant	-0.036969	0.020714	-1.784731	0.0743
	LDS (-1)	-0.519201	0.032389	-16.03022	0.0000
	Variance Equation				
	Constant	0.285886	0.018377	15.55678	0.0000
	RESID (-1)^2	0.151475	0.042805	3.538717	0.0004
	RESID (-2)^2	0.257489	0.050674	5.081296	0.0000
	RESID (-3)^2	0.085143	0.029572	2.879216	0.0040

Models Diagnostics and Selection

The ARCH-LM test was conducted for both GARCH (1, 1) and ARCH (3) or GARCH (0, 3) to determine whether heteroscedasticity still existed in both models up to lag 36. Table 4 presented the diagnostic results of the ARCH-LM test for both models. The test results indicated that GARCH (1, 1) model was the optimal model. The LM-statistic = 31.20; $p = 0.70 > 0.05$. for GARCH (1, 1) and the comparative LM-statistic for ARCH (3) = 53.48; $p = 0.03 < 0.05$. Thus, the ARCH-LM test results for both models indicated that there was no more existing heteroscedasticity in GARCH (1, 1) model. Finally, testing GARCH (1, 1) model for serial correlation, the correlogram of standardized residuals squared indicated all lags to be non-significant or within the standard error bounds (p -values > 0.05) even up to lag 36. The serial correlation test results failed to reject the null hypothesis of *no autocorrelation* in the model. Figure 3 showed the correlogram of standardized residuals squared for GARCH (1, 1) model.

Sample: 1/01/2020 6/30/2022
Included observations: 910

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob*
		1 0.047	0.047	1.9891	0.158
		2 0.049	0.046	4.1425	0.126
		3 0.018	0.014	4.4529	0.217
		4 -0.025	-0.029	5.0198	0.285
		5 0.000	0.001	5.0198	0.413
		6 -0.023	-0.021	5.5109	0.480
		7 -0.052	-0.049	7.9963	0.333
		8 -0.030	-0.025	8.8334	0.357
		9 0.012	0.020	8.9681	0.440
		10 -0.058	-0.056	12.029	0.283
		11 -0.010	-0.009	12.124	0.354
		12 0.014	0.018	12.300	0.422
		13 -0.041	-0.042	13.877	0.383
		14 -0.020	-0.025	14.265	0.430
		15 -0.028	-0.025	14.970	0.454

Figure 3: Correlogram of standardized residuals squared for GARCH (1, 1) for 15 lags

Table 5: ARCH-LM test for selected competitive models

Model				p-value
GARCH (1, 1)	F-statistic	0.860691	Prob. F (36,837)	0.7034
	Obs*R-squared	31.19959	Prob. Chi-Sq (36)	0.6962
GARCH (0, 3)	F-statistic	1.515430	Prob. F (36,837)	0.0279
	Obs*R-squared	53.48122	Prob. Chi-Sq (36)	0.0305

The mean and variance equations of the optimal model GARCH (1, 1) include:

Mean equation

$$lds_t = -0.012803 + -0.478049lds_{t-1} \quad (12)$$

Variance equation

$$GARCH(1, 1) = 0.001592 + 0.053825\hat{u}_{t-1}^2 + 0.927965\hat{\sigma}_{t-1}^2 \quad (13)$$

(1.3895) (5.2656) (112.56)

Where $0 < \alpha_1 < 1$, $0 < \beta_1 < 1$, $\alpha_1 + \beta_1 \leq 1$ and $\alpha_0 \geq 0$ in model (13)

GARCH (1, 1) Volatility Forecasting

Figure 4 depicted the static forecast of the entire period emergency services demand variance using GARCH (1, 1) while Figure 5 depicted the static forecast of the last three-month short-term period.

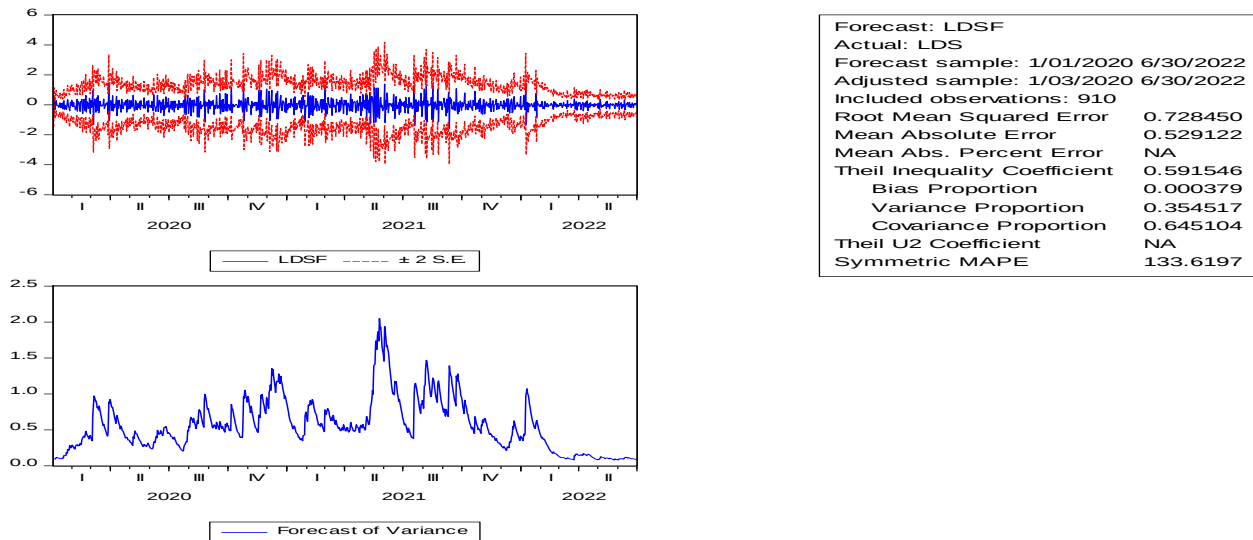


Figure 4: Full sample static forecast of volatility using GARCH (1, 1) model

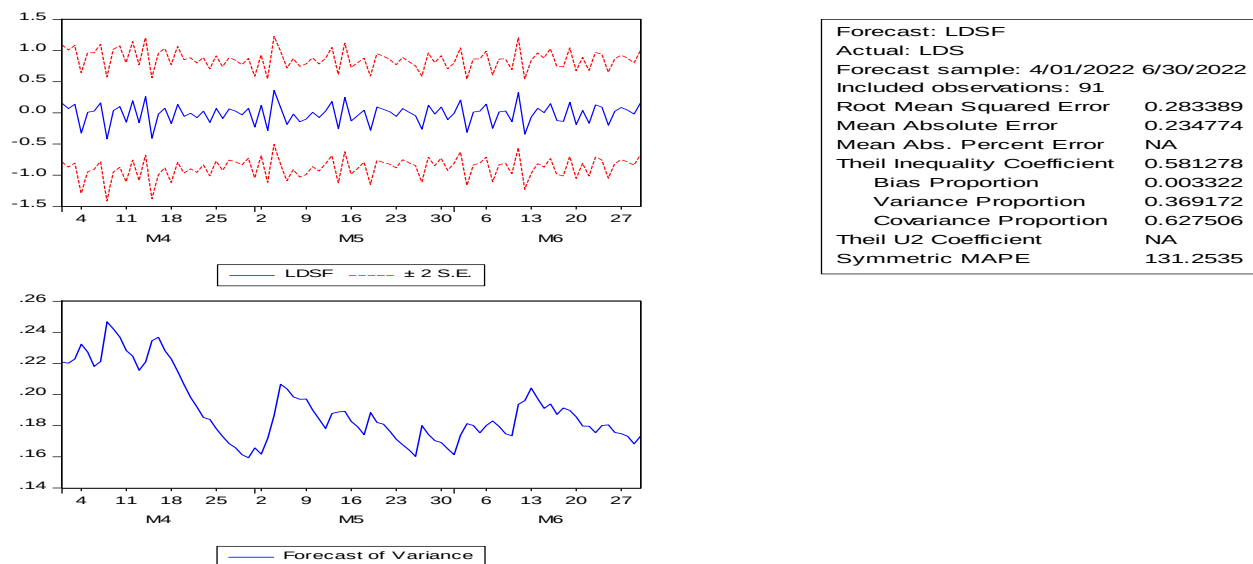


Figure 5: Modified sample (Q2, 2022) static forecast of volatility using GARCH (1, 1) model

DISCUSSIONS

The emergency healthcare industry worldwide has witnessed an increasing demand for emergency healthcare, registering an annual average growth rate of 2.4% over the past decade, and is therefore sensitive and designing systems and structures for timely response to emergency incidents as well as epidemiological events as concurred in other research study results [11, 12, 19]. The study results showed a total of 13,656 emergency visits over the period of January 2020 through June 2022 with almost half (6,296 emergency visits) recorded in the 1st and 2nd quarters of 2022. Current daily average admissions of 35 patients in an 11-bed capacity ward with a return series exhibiting intense and persistent volatility indicated prevalence of inadequacy in readiness in the system, and hence, this should prompt early corrective action.

Figures 1&2 graphically demonstrated the existence of volatility clustering in the return series of the daily demand for emergency healthcare services in the hospital as high volatile periods were followed by high volatile periods with low volatile periods followed by low volatile periods (see fig. 1) and also the distribution of the return series for the demand was leptokurtic (see fig. 2) with fat tails and the Jarque-Bera (JB) statistic = 150.34, $p < .001$ indicating non-normality of the distribution [2, 3]. Similarly, the 'forecast of variance' graph (see fig. 4) for the entire study period exhibited time-varying variance. The formal test for the existence of autoregressive conditional heteroscedasticity (ARCH) as shown in Table 2 confirmed the existence of heteroscedasticity. The observed R-squared statistic was very significant as shown in Table 2. The corresponding LM-statistic = 20.15, $p < .001$. Therefore, the null hypothesis that there are no existing ARCH effects in the system was rejected. This simply means that past innovations (shocks) have an effect or a relationship with the system's future innovations. Hence, these effects were then estimated and modeled using the GARCH family models.

Under the estimation of the ARCH effects in the system six candidate models including one ARCH and five GARCH models were considered for selection. ARCH (3) and GARCH (1, 1) emerged with superior characteristics after a comprehensive assessment and had their

respective model details presented in Table 4. Model diagnostics was conducted on both models and GARCH (1, 1) emerged as the optimal model for forecasting volatility. In Table 4, the mean equation of the optimal model, GARCH (1, 1), had negative coefficients with the immediate past value of the dependent variable significantly predicting the current value of the series. Analytically, the z-statistic = -16.83827, $p < .001$. Hence, the implication here is that the past value of the dependent variable (returns of daily demand for emergency healthcare services) had significant influence on the current value of the series. On the other hand, the coefficients of the variance equation are all positive with both the ARCH and GARCH coefficient terms highly statistically significant. Equation (13) presented the result of the optimal model GARCH (1, 1) that mitigated the existing heteroscedasticity with its mean equation in (12). All coefficients of the estimated optimal model GARCH (1, 1) met the stability conditions [1, 2, 18]. Hence, the sum of the coefficients on the lagged squared error and lagged conditional variance is very close to unity (approximately 0.98). This implies that shocks to the conditional variance will be highly persistent. Hence, the impact of today's shock remains in the system and does not die but is absorbed in the forecast of variance for the demand for daily emergency healthcare services for many periods in the future [17].

The forecast of the conditional variance as shown in Figure 4 revealed that the returns of the demand for emergency healthcare services in the hospital exhibited intense and persistent volatility with few pockets of stability throughout the system. Hence, this phenomenon should not be unexpected in the returns of future demand for emergency healthcare services in the hospital. The results indicate confirmation of the findings of studies such as [10, 11, 12] which suggest that most reported emergency cases in the major hospitals in Ghana are volatile and are due to road traffic accidents and falls, accounting for about 60% of all emergency cases. The increased in demand for emergency healthcare in these occasions often stretched the already weak and vulnerable [12] emergency healthcare system to its limits thereby creating losses or liabilities, negative spillover effects, medicinal supply chain disruptions, overall costs, and exposure of professionals to greater workload and its attended repercussions such as possible increased professional burnout [20-22].

On the modified period forecast of the conditional variance (see fig. 5), the returns of the demand are shown to have remained stable with minimized volatility setting toward the end of the study period. However, it is highly probable that future returns of daily demand for emergency healthcare services in the hospital would show intense and persistent volatile periods and every due preparation should be made in order to mitigate any expensive disruptions in the delivery of prudent emergency healthcare services in the hospital. By implication, the emergency unit should be built or restructured with a higher number of available beds than currently exist in practice to curtail the existing and persistent volatilities. Also, risk management practices and supporting methods need to be designed and developed to allow the hospital management to staff the occupied beds in a predictive manner rather than the available beds in order to minimize overall costs and risks and ultimately maximize quality patient care.

Limitations: It must be noted, however, that ARCH and GARCH models are inevitably data-intensive and often require decades of high and uninterrupted frequency data for excellent results. However, these requirements were empirically highly improbable and hence a

limitation. It must also be noted that the findings of this study are only limited to the University of Cape Coast hospital setting and not beyond.

CONCLUSION

The study evidence demonstrated empirically the existence and persistence of high volatility clustering in the returns of the daily demand for emergency healthcare services in the University of Cape Coast hospital. Findings present to management the erratic behavior of the returns of daily demand for emergency healthcare services in the hospital, measured and quantified the degree of exposure to volatility clustering, and finally forecast the existing and persistent volatility clustering. Hence, the volatile demand for emergency healthcare services in the university hospital should be equilibriate by an effective, and efficient supply system to avoid a likely expensive disruption or system's structural failure in the course of the delivery of the vital services.

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