International Journal of Innovative Research and Advanced Studies (IJIRAS)
Volume 3 Issue 5, May 2016

ISSN: 2394-4404

Demand For Life Insurance Products In The Upper East Region Of Ghana

Abonongo John

Department of Mathematics,
Kwame Nkrumah University of Science and Technology,
Kumasi, Ghana

Luguterah Albert

Department of Statistics,
University for Development Studies,
Navrongo, Ghana

Abstract: Life insurance policies provide benefits that are contingent on the survival of the policyholder for a certain period, or on the death of the policyholder within a certain period. One of the prudent decision(s) an individual or families undertake is whether to purchase Life insurance product or not. This decision is to protect the individual against any uncertainty during retirement or in the case of death or otherwise. This paper tends to establish the relationship between the demands for Life insurance products among four insurance companies in the Upper East Region of Ghana. The insurance companies were State Insurance Company (SIC), Quality Life Assurance, Glico Life Insurance and Star Life Insurance. The studies revealed that, the growth rate of each insurance company was independent of the other; thus the number insured for one insurance company was not directly influenced by the number insured of another insurance company. This was supported by the VAR (1) model and the Granger causality analysis employed. In effect, the number of insured for each insurance company were the same policyholders who advocated for other people to get insured and that the insurance companies marketing strategies were also at par. It was also revealed that, the Life insurance penetration kept on improving in the Upper East Region since the number insured kept on increasing.

Keywords: Life insurance demand, insured, policyholders, life insurance product

I. INTRODUCTION

The demand for Life insurance has generally been modeled in the life cycle framework in which households maximize the expected utility of their lifetime consumption. Yaari, (1965), Hakansan, (1969), Fischer, (1973), and Campbell, (1980) assumed that households receive uncertain income streams owing to the wage earners likelihood of untimely death. Life insurance is used as a toolfor working towards reducing the volatility of household consumption. Uncertainty surrounding lifetime expectancy thus directs the consumption of life insurance. In a recent survey, Ziet (2003) list studies documenting the positive association between risk aversion and life insurance consumption.

Considerable evidence suggests that many people for whom insurance is worth purchasing do not have coverage and others who appear not in need of financial protection against certain events actually have purchased coverage. There are certain types of measures for which one might expect to see insurance widely marketed, that are viewed today by insurers as uninsurable and there are other policies one might not expect to be successfully marketed that exist on a relatively large scale. In addition, evidence suggests that cost-effective preventive measures are sometimes not rewarded by insurers in ways that could change their clients' behaviour, (Kunreuther and Pauly (2004)).

Using the expected utility framework in a continuous time model, Yaari, (1965) studied the problem of uncertain lifetime and life insurance. Including the risk of dying in the life cycle model, he showed conceptually that a person increases expected lifetime utility by purchasing fair life insurance and fair annuities. Simple models of insurance demand were proposed by Mossin, (1968) and others; considering a risk averse decision maker with an initial wealth *W*. The results indicated that, demand for life insurance varies inversely with the wealth of the individuals.

Burnet and Palmer, (1984) examined psychographic and demographic factors and found that, work ethic and religion as well as education and income, among other characteristics were significant factors of life insurance demand.

The study by Browne and Kim, (1993) expanded the discussion on life insurance demand by adding newer variables namely; average life expectancy and enrollment ratio of third level education. The study based on 45 countries for two separate time periods (1980 and 1987) concluded that, income and social security expenditures are significant determinants of insurance demand, however, inflation has a negative correlation. Dependency ratio, education and life expectancy were not significant but incorporation of religion, a dummy variable, indicates that Muslim countries have negative affinity towards life insurance.

Allowing income elasticity to vary as GDP grows for an economy, Enz, (2000) proposed the *S*-curve relation between per-capital income and insurance penetration. Using this one factor model one can generate long run forecast for life insurance demand. Observing the outlier countries or countries distant from the S-curve plot, it is possible to identify structural factors like insurance environment, taxation structures, etc. resulting in such deviations.

This paper investigated the relationship between Life insurance demand among four insurance companies in the Upper East Region of Ghana since not much studies has carried out on this in Ghana and the Upper East Region in particular. This research will give policyholders in the insurance industry to improve their marketing strategies and improve penetration in the Upper East Region of Ghana.

II. METHODOLOGY

A. DATA AND SOURCE

This study used data on the monthly number of clients who purchased life insurance policies from four insurance companies namely; Glico Life Insurance, State Insurance Company, Quality Life Assurance and Star Life Insurance in the Upper East Region of Ghana from the period 2006-2011.

B. UNIT ROOT TEST: STATIONARITY TEST

Analysis using non-stationary time series variables generally produce fictitious regression since standard results of OLS do not hold. It is therefore vital in time series data analysis to check for the presence or absence of unit root in the series being studied. The two quantitative stationarity tests used in this research are; the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The ADF test uses the hypothesis;

$H_0: \theta = 1$ (Non − stationary) against
$H_1: \theta < 1$ (Stationary)

where θ is the characteristic root of an *AR* polynomial and u_t is assured to be white noise series. The ADF test statistic is given as;

$$F_\tau = \hat{\emptyset} / SE(\hat{\emptyset}) \quad (1)$$

where $\hat{\emptyset} = \theta - 1$ is the parameter estimate of $\emptyset$ and $SE(\hat{\emptyset})$ is the standard error of $\hat{\emptyset}$. The null hypothesis (H_0) is rejected if a significant ADF test statistic is obtained ($p - value < \alpha$ (significance level)). Although the ADF test corrects for serial correlation, conditional heteroscedasticity in the residual term of the ADF model may still posed a problem, the Phillips and Perron, (1988) semi-parametric test for unit root corrects for any serial correlation and conditional heteroscedasticity in the error term, u_t, non-parametrically. The PP test used the model;

$$R_t = \alpha t + \rho r_{t-1} + u_t \quad (2)$$

with test statisticsgiven as;

$$Z_\rho = n(\hat{\rho}_n - 1) - 1/2 \frac{n^2 \hat{\sigma}^2}{s_n^2} (\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}) \quad (3)$$

Which corrects for conditional heteroscedasticity in the residual term and

$$Z_\tau = \sqrt{\frac{\hat{\gamma}_{0,n}}{\hat{\lambda}_n^2}} \times \frac{\hat{\rho}_n - 1}{\hat{\sigma}} - 1/2 (\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}) \frac{1}{\hat{\lambda}_n} \frac{n\hat{\sigma}}{s_n} \quad (4)$$

Which corrects for serial correlation in the residual term.

$\hat{\gamma}_{j,n} = 1/n \sum_{i=j+1}^{n} \hat{u}_i \hat{u}_{i-j}$, and $\hat{\lambda}_n^2 = \hat{\gamma}_{0,n} + 2\sum_{j=1}^{q} (1 - \frac{j}{q+1}) \hat{\gamma}_{j,n}$, if there is no autocorrelation between the residual terms, $\hat{\gamma}_{j,n} = 0$ for $j > 0$, then $\hat{\lambda}_n^2 = \hat{\gamma}_{0,n}$, therefore, Z_τ, becomes

$Z_\tau = \frac{\hat{\rho}_n - 1}{\hat{\sigma}}$,thus the standard Dickey-Fuller (DF) equation. Also, for an equal covariance, then $\hat{\lambda}_n^2 = \hat{\gamma}_{0,n}$, the residual terms are homoscedastic, therefore $Z_\rho = n(\hat{\rho}_n - 1)$ is the same as the DF test. Hence if there is no autocorrelation and conditional heteroscedasticity between the residual error terms, the PP test is equal to the DF statistic with constant and time trend. $s_n^2 = \frac{1}{n-k} \sum_{i=1}^{n} \hat{u}_i^2$ is the (OLS) unbiased estimator of the variance of the residual error term u_i, *k* is the number of covariates in the regression, *q* is the number of Newey-West lags to use in the calculation of $\hat{\lambda}_n^2$ and $\hat{\sigma}$ is the OLS standard error of $\hat{\rho}$.

C. MULTIVARIATE TIME SERIES

Multivariate time series is used in situations where variable depends on its own past and on the past values of other variables. Multivariate analysis was used in this study since there is the consideration of four insurance companies altogether. The fundamental model in multivariate time series analysis is vector autoregressive (VAR) which focus on analyzing covariance stationary multivariate time series variables. The vector auto regression (VAR) model helps in interpreting the dynamic relationship between set of indicate variables and thus determine whether one variable is suitable in predicting another variable. In this paper, the data on the number of purchases of insurances policies of each company used for fitting the VAR model was transmuted to obtain the growth rates given by;

$$GR = (ln b_t - \ln b_{t-1}) \times 100$$

where b_t the number of purchases of an insurance claim at time *t* and b_{t-1} is the number of purchases f an insurance claim at time $t-1$. Let $B_t = (b_{1t}, \ldots, b_{nt})'$ be an $(n \times 1)$ vector of time series variables. A *p*-lag vector autoregressive (VAR (*p*)) model has the form;

$$B_t = U + \beta_1 b_{t-1} + \cdots \ldots \ldots \ldots + \beta_p b_{t-p} + \varepsilon_t, \quad t = 0,1,\ldots,T$$

where $B_t = (b_{1t}, \ldots, b_{nt})'$ is a $(n \times 1)$ random vector of the insurance companies, $\beta_i, i = 1, \ldots, p$ is an $(n \times n)$ parametermatrices, $U = (U_1, \ldots, U_n)$ is a $(n \times 1)$ vector of intercept and $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{nt})'$ is an $n \times 1)$ unobservable zero mean white noise vector process (serially uncorrelated or independent)with time invariant covariance matrix Σ. The VAR (*p*) is stable if the roots of $det(I_n - \beta_1 z^1 - \cdots - \beta_p z^p) \neq 0$ lie outside the complex unit circle (have modulus greater than one (1)) or if the eigenvalues of the companion matrix have modulus less than one (1).

D. LAG ORDER SELECTION

The lag length for the VAR(*p*) model is determined using three model selection criteria. This is done by fitting the VAR(*p*) models with orders $p = 0, \ldots, p_{max}$ and the value of p which minimizes these model selection criteria is chosen. The criteria are given as;

$$AIC = ln\left|\widetilde{\sum_{\varepsilon}}(p)\right| + \frac{2}{T}pn^2 \qquad (5)$$

$$HQIC = ln\left|\widetilde{\sum_{\varepsilon}}(p)\right| + \frac{2\, ln\{ln(T)\}}{T}pn^2 \qquad (6)$$

$$SBIC = ln\left|\widetilde{\sum_{\varepsilon}}(p)\right| + \frac{ln(T)}{T}pn^2 \qquad (7)$$

where T denotes the number of observations in the data, p assigns the lag order, $\widetilde{\sum_u}(p) = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t'$ is the residual covariance matrix with uncorrected *df*.

E. VAR MODEL (S) DIAGNOSTICS

To use a fitted model for statistical inference, it is essential to diagnose the model to determine whether the model best fit the series. Thus, if the residuals of the fitted model were white noise series. This study therefore employed the univariate and multivariate Ljung-Box test to check for serial correlation the residuals of the fitted models and the ARCH-LM test to test for conditional heteroscedasticity in the residuals of the fitted models.

F. GRANGER CAUSALITY TEST

If a time series variable, or group of time series variables B_1, is found to be helpful for predicting another time series variable, or group of time series variables, B_2, then B_1 is said to Granger-cause B_2; otherwise it fail to Granger-cause B_2. Formally, B_1 fails to Granger-cause B_2 if for all s > 0 $\text{MSE}_f(B_2, t+s)$based on $(B_2, t, B_2, t-1, \ldots) \leq \text{MSE}_f(B_2, t+s)$ based on $B_2, t, B_2, t-1, \ldots)$ and $B_1, t, B_1, t-1, \ldots)$.

G. FORECAST ERROR VARIANCE DECOMPOSITION (FEVD) ANALYSIS

The forecast error variance decomposition (FEVD) answers the question:what portion of the variance of the forecast error in predicting $B_i, T+h$ is due to the structural shock η_j? Using the orthogonal shocks η_t the h-stepahead forecast error vector, with known VAR coefficients, may be expressed as:

$$FEVD_{i,j}(h) = \frac{\sigma_{\eta_j}^2 \sum_{s=0}^{h-1}(\theta_{ij}^s)^2}{\sigma_{\eta_1}^2 \sum_{s=0}^{h-1}(\theta_{i1}^s)^2 + \ldots + \sigma_{\eta_n}^2 \sum_{s=0}^{h-1}(\theta_{in}^s)^2} i,j = 1,2,\ldots,n \qquad (8)$$

where $\sigma_{\eta_j}^2$ is the variance of η_{jt}.

H. IMPULSE RESPONSE FUNCTION (IRF) ANALYSIS

The impulse response analysis is employed to further investigate the changes in the endogenous time series variables and is centered on the Wold's moving average representation of a VAR (p) process. It helps in determining the response of one time series variable to an impulse or shock in another time series variable.

The Wold representation is centered on the orthogonal error ε_t given by;

$$B_t = \alpha + \beta_0\varepsilon_t + \beta_1\varepsilon_{t-1} + \beta_2\varepsilon_{t-2} + \cdots$$

where β_0 is a lower triangular matrix. The impulse response to the orthogonal shocks ε_{jt} are;

$$\frac{\partial B_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial B_{i,t}}{\partial \varepsilon_{j,t-s}} = \varepsilon^2{}_{ij} \quad i,j = 1,2\ldots,k,s, > 0$$

where $\varepsilon^2{}_{ij}$ is the $(i,j)th$ element of β_0. For n variables there are n^2 possible IRF.

III. ANALYSIS OF RESULTS

A. DESCRIPTIVE STATISTICS

Table 1 shows the summary statistics of the original series of the four insurance companies. It was realized all the variables were positively skewed indicating that the number of client (insured) for each insurance company increased continuously over time. The excess kurtosis for the four insurance companies was positive showing that they are leptokurtic in nature and more peaked compared to the normal distribution. Comparing the coefficient of variation for all companies, SIC Life Insurance stands more volatile in terms of the number insured compared to the rest. This was supported by the excess kurtosis, SIC Life Insurance stands to be more volatile indicating that the number insured for Life policies keeps changing compared to the rest of the companies.

ADF Test					PP TEST	
Category	Only Constant		Constant and Trend			
	Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value
Quality Life Assurance	-0.648	0.858	-3.635	0.057	-0.843	0.806
Glico Life Insurance	-1.721	0.421	-2.469	0.344	-0.090	0.950
Star Life Insurance	-0.361	0.913	-1.835	0.688	-0.311	0.924
SIC Life Insurance	-0.459	0.897	-6.005	0.613	-3.156	0.063

Table 1: Summary Statistics

From the time series plot for the insurance companies in Fig 1, the number of clients for all the insurance companies increases and decreases over time. There are major decreases for quality life assurance for 2006 and 2008 and major increases for 2009 and 2010. This shows that the number of clients for Quality Life Assurance changes over time with an increasing client number from 2010 upwards. Glico Life Insurance had a major increase in 2006 and from 2009-2010. There were major decreases in the number of clients from 2007-2008. This shows that the number of clients for Glico keeps fluctuating over time. For Star Life Insurance, the time series plot indicates major increases and decreases from 2006-2010 with 2009and 2010 having fewer increases in the number clients hence the number of clients changing over time. For SIC Life Insurance, the plot shows that the company had drastic decreases from 2006-2008 and some major increases from 2008-2010.

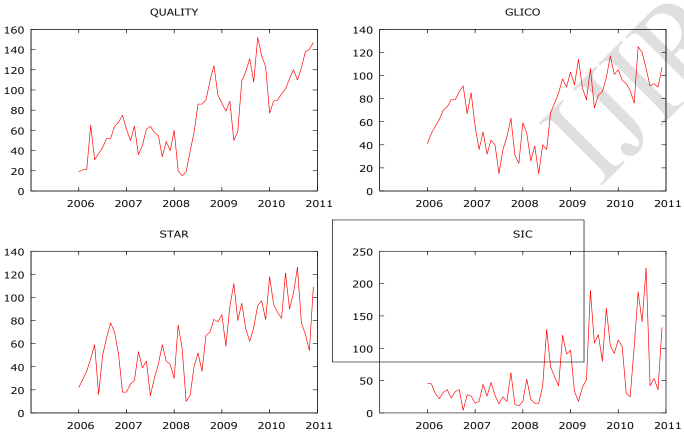

Figure 1: Time Series Plot of Original Data of Insurance Companies

B. FURTHER ANALYSIS

The ADF test and PP test was conducted on the original series to confirm the non-stationarity otherwise in the number of insured for each company. As indicated in Table 2, an insignificant ADF test and PP test statistics was obtained for the number of insured for the four companies at the 5% significant level. This leads to the failure to reject the null hypothesis that the series is non-stationary, therefore showing the existence of unit root in the number insured for each company and that the individual insured rate are individually not covariance stationary. This was also depicted from the time series plots in Fig 1, showing the various fluctuations levels in the original series. Since the original series is non stationary, further analysis with it makes the ordinary least square (OLS) estimate unable to retain its asymptotic and leads to fallacious results (Granger and Newbold, 1974; Phillips, 1986).

Company	Mean	Std.Dev	CV	Variance	Skewness	Kurtosis
Quality Life Assurance	85.550	41.593	48.618	1729.941	0.663	3.316
Glico Life Insurance	90.000	48.591	53.990	2361.775	0.567	2.791
Star Life Insurance	81.014	51.503	63.573	2652.521	0.978	3.426
SIC Life Insurance	73.597	62.373	84.749	3890.357	1.223	3.917

Table 2: ADF and PP Unit Root Test of Original Series

The growth rates of the series were estimated and stationarity tested using ADF and PP tests. The two tests as indicated in Table 3, shows that the number of insured for the four companies was stationary at 5% significant level. Taking the growth rate stabilizes the mean and variance making the series covariance stationary.

ADF Test of the Growth Rates					PP TEST	
Category	Only Constant		Constant and Trend			
	Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value
Quality Life Assurance	-4.145	0.002	-4.271	0.007	-3.294	0.002
Glico Life Insurance	-1.450	0.034	-1.656	0.019	-5.722	0.000
Star Life Insurance	-6.960	$1.125e^{007}$	-7.026	$8.103e^{007}$	-6.408	0.000
SIC Life Insurance	-3.049	0.031	-2.887	0.027	-9.296	0.000

Table 3: ADF and PP Test for the growth rate for each insurance company

To obtain the appropriate maximum lag order to be used in the VAR model, the AIC, SBIC and HQIC information criteria was employed. From Table 4, the SBIC and HQIC criteria were selected as the optimal lag for the VAR model since the lag order one (1) had the least SBIC value of 8.011 and HQIC value of 7.563, whiles AIC criterion selected lag 3. Since the SBIC and HQIC are consistent estimators, the lag one (1) selected by them was considered.

Lag	AIC	SBIC	HQIC
1	7.281	8.011*	7.563*
2	7.538	8.852	8.046
3	7.262*	9.160	7.996
4	7.424	9.906	8.383
5	7.347	10.413	8.532

**means Lag selected by criterion*

Table 4: Lag Order Selection for Fitting VAR Model

Table 5 shows the fitted VAR (1) model to check whether or not the past values of the number insured of one or more insurance company had an impact on another insurance company. Thus the number of past life policy holders of an insurance company could predict the number of insured for the other companies. The estimates indicated in Table 5 showed that, the growth rate in the number of clients for Glico Life Insurance, Star Life Insurance and SIC Life Insurance, have no effect on the growth rates of the number of clients of each of the other companies. Also the number insured for Quality life Assurance was influenced by its own past values and that the number life policy holders are thus influenced by the number of its past policy holders. The estimate of the growth rate for Quality Life Assurance, Star Life Insurance and SIC Life Insurance are not useful in predicting the growth rate in the number of clients for Glico Life Insurance at 5% significant level. But the number insured for this Life policy depended on its past number insured for the Life products. Star Life Insurance's growth rate was statistically not influenced by Glico Life Insurance, Quality Life Assurance and SICS Life Insurance. This shows that, the number insured for Star Life Insurance cannot be predicted by the past values of the other three insurance companies. Also, the growth rate of Glico Life Insurance, Quality Life Assurance and Star Life Insurance are not statistically useful in predicting the growth rate of SIC Life Insurance. In the nutshell, the growth rate of one insurance company was independent of the growth rate of another insurance company, thus the number of clients of each insurance company is not affected by the number of clients of each of the other companies.

This further indicates that, the number of clients an insurance company depends solely on its own ability to appropriately market its insurance products or policies to the general public. Also, it may depend on it previous clients who advise friends and families to obtain an insurance policy from a particular insurance company.

Equation	Variables	Coefficient	S.E	t-ratio	P-value
Quality Life Assurance	Constant	-0.033	0.096	-0.343	0.733
	Quality Life Assurance.1	-0.249	0.293	-0.849	0.020**
	Glico Life Insurance.1	-0.085	0.275	-0.311	0.757
	Star Life Insurance.1	-0.220	0.202	-1.089	0.281
	SIC Life Insurance.1	-0.142	0.132	-1.080	0.287
Glico Life Insurance	Constant	-0.060	0.093	-0.650	0.519
	Quality Life Assurance.1	0.130	0.283	0.458	0.648
	Glico Life Insurance.1	-0.434	0.265	-1.638	0.004**
	Star Life Insurance.1	-0.060	0.194	-0.307	0.760
	SIC Life Insurance.1	-0.095	0.127	-0.747	0.458
Star Life Insurance	Constant	-0.064	0.100	-0.639	0.526
	Quality Life Assurance.1	0.378	0.304	1.241	0.220
	Glico Life Insurance.1	0.335	0.285	1.175	0.245
	Star Life Insurance.1	-0.292	0.209	-1.394	0.032**
	SIC Life Insurance.1	-0.207	0.137	-1.515	0.136
SIC Life Insurance	Constant	-0.070	0.129	-0.541	0.591
	Quality Life Assurance.1	0.349	0.392	0.890	0.377
	Glico Life Insurance.1	-0.053	0.367	-0.145	0.885
	Star Life Insurance.1	0.074	0.270	0.275	0.784
	SIC Life Insurance.1	-0.445	0.176	-2.523	0.015**

Table 5: Fitted VAR (1) Model

A stability test was performed on the fitted VAR (1) model fitted to check the whether or not the parameters were structural stable over time. From Table 6, the estimates shows that the VAR (1) model parameters are structurally stable since all the eigenvalues obtained are less than one (1) in modulus. This indicates that the growth rate employed in fitting the VAR (1) model was covariance stationary as indicated in ADF and PP tests in Table 3.

Variable	Eigenvalues	Modulus
Quality Life Assurance	-0.326+0.4090i	0.523
Glico Life Insurance	-0.326-0.4651i	0.523
Star Life Insurance	-0.465	0.465
SIC Life Insurance	-0.302	0.302

All the eigenvalues lie inside the unit circle.

Table 6: VAR (1) Model Stability Test

A univariate and multivariate model diagnosis were employed in checking for the adequacy of the VAR (1) model. In Table 7, the univariate Ljung-Box test indicated that at lag 12 and 24 the residuals of the four individual models or equations were free from serial correlation since the p-values of the chi-square statistics exceeds 5% significant level. From the ARCH-LM test in Table 7, it was also seen that, the ARCH-LM test fails to reject the null hypothesis of no ARCH effect in the residuals of the four models since the p-values are greater than the 5% significant level. This shows that the residuals were free from conditional heteroscedasticity and thus the residuals are uncorrelated thus are White noise series.

	Ljung-Box Test			ARCH-LM Test	
Equation	Lag	Test Statistics	P-value	Test Statistics	P-value
Quality Life Assurance	12	2.128	0.999	3.117	0.995
	24	7.203	1.000	13.370	0.960
Glico Life Insurance	12	3.903	0.985	4.604	0.967
	24	4.680	1.000	14.220	0.942
Star Life Insurance	12	4.474	0.973	1.999	0.999
	24	918.371	0.999	4.899	1.000
SIC Life Insurance	12	15.886	0.197	12.807	0.383
	24	23.647	0.482	24.323	0.443

Table 7: Univariate Ljung-Box Test and ARCH-LM Test of VAR(1) Models

The residual plots of the individual VAR (1) models in Fig 2 indicates that, the residuals of Quality Life Assurance, Glico Life Insurance, Star Life Insurance and SIC Life Insurance equations are white noise series since the residual have a constant variance and zero mean.

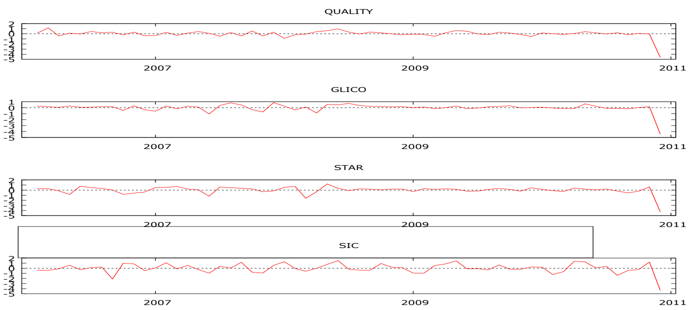

Figure 2: Residual Plots of the Individual VAR (1) Models

International Journal of Innovative Research and Advanced Studies (IJIRAS)
Volume 3 Issue 5, May 2016

ISSN: 2394-4404

Additionally in Table 8, multivariate Lung-Box and ARCH-LM tests performed showed that, the residuals of the VAR(1) model were uncorrelated and have a constant variance, thus are white noise series.

		Ljung-Box Test		ARCH-LM Test	
Equation	**Lag**	**Test Statistic**	***p*-value**	**Test Statistic**	***p*-value**
VAR(1) model	12	22.305	0.541	1050.000	0.992
	24	15.216	0.974	983.000	1.000

Table 8: Multivariate Ljung-Box Test and ARCH-LM Test of VAR (1) Model

The VAR (1) was used investigate Granger causality among the growth rates of the insurance company to find out which variable(s) can further improve in predicting the growth rate of the other insurance companies over time. From the Granger causality test in Table 9, SIC Life Insurance, Glico Life Insurance and Star Life Insurance and their linear combination does not Granger cause Quality Life Insurance. The insignificant chi-square statistics obtained for each growth rate and as well as their linear combinations at 5% significant level shows that there is no relationship between the growth rates of Quality Life Insurance and the other three insurance companies and that the growth rates in these companies cannot enhance prediction of the growth rates in Quality Life Insurance. The results also indicates that, the growth rates in Quality Life insurance, SIC Life insurance and Star Life insurance does not Granger cause the growth rates in Glico Life insurance. This is indicated by the chi-square statistics obtained for each growth rate and their linear combination which are not significant at 5% significant level. This implies that, none of these insurance companies and their combination can improve the prediction of Quality Life insurance. Also, the growth rates of Star Life insurance is not influenced by any of the other three insurance companies. The chi-square statistics estimated for each individual growth rates of the insurance companies and their linear combination are insignificant at 5% significant level. It adds to it that the growth rates of Glico Life Insurance, Quality Life Insurance and SIC Life Insurance does not improve the prediction of the growth rate of Star Life Insurance. There is an insignificant chi-square statistics for the individual growth rate of the companies at 5% significant level. Also the growth rate of Quality Life Assurance, Star Life Insurance and Glico Life Insurance does not Granger-cause the growth rates of SIC Life Insurance. These results support the results of the VAR(1) that the number of clients insured for an insurance company is independent of the others.

Equation	Excluded	χ^2	df	Prob.
Quality Life Assurance	Glico Life Insurance	0.106	1	0.757
	Star Life Insurance	1.265	1	0.281
	SIC Life Insurance	1.296	1	0.287
	All	4.220	3	0.239
Glico Life Insurance	Quality Life Assurance	0.230	1	0.649
	Star Life Insurance	0.610	1	0.760
	SIC Life Insurance	0.103	1	0.458
	All	1.297	3	0.730
Star Life Insurance	Quality Life Assurance	1.682	1	0.220
	Glico Life Insurance	1.508	1	0.245
	SIC Life Insurance	2.509	1	0.136
	All	5.538	3	0.136
SIC Life Insurance	Quality Life Assurance	0.866	1	0.377
	Glico Life Insurance	0.023	1	0.885
	Star Life Insurance	0.083	1	0.784
	All	0.883	3	0.830

Table 9: Granger Causality Wald Test

The reaction of the number insured (growth rate) in the model following a sudden change in the VAR (1) model was also investigated as shown in Figure 3.When the impulse was Quality Life Assurance, in the first period, Quality Life Assurance reacted positively to the shock in its own values until the second period where it reacted negatively. There was a stable reaction period 3-4 with sudden negative reaction in period 4-5. Glico Life Insurance reacted positively to the shock in Quality Life Assurance in the first period until the second period where it reacted negatively with a much stable reaction from period 3-5. Star Life Insurance reacted positively in the first period and negative reaction from period 2-3 with sudden negative reaction from period 4-5. SIC Life Insurance reacted positively in the first period until period 2-5 where there was a sudden negative reaction. When the impulse was Glico Life Insurance, Quality Life Insurance reacted positively in the first period until period 2. It reacted positively from period 2-3 and a negative reaction from period 3-5. Glico Life Insurance reacted positively to its own shocks at period 1 and 3 and a stable respond from 4-5. Star Life Insurance reacted positively to the innovation in Glico Life Insurance in the first period and continued with negative reactions from period 2-3 with negative reactions from period 4-5. SIC Life Insurance also reacted positively in the first period with a negative reaction in period 2 and a stable from period 3-5. When the impulse was Star Life Insurance, Quality Life Assurance reacted positively to innovations in Star Life Insurance for the first period and a negative response for period 2, positive response for 2-3, decline for 4 and stable for 5. Glico Life Insurance reacted positively from 2-3 and negatively from period 3-5. Star Life Insurance reacted positively in its own innovations until from period 3-5 where the response was approximately stable. SIC Life Insurance also reacted positively in the first period and a negative reaction from period 4-5. When the impulse was SIC Life Insurance, Quality Life Assurance reacted negatively in the first period until from period 2-3 where there was a positive response. Glico Life Insurance also reacted negatively in the second period with a positive response from period 2-3. Star Life Insurance responded negatively in the second with positive response from period 2-4.

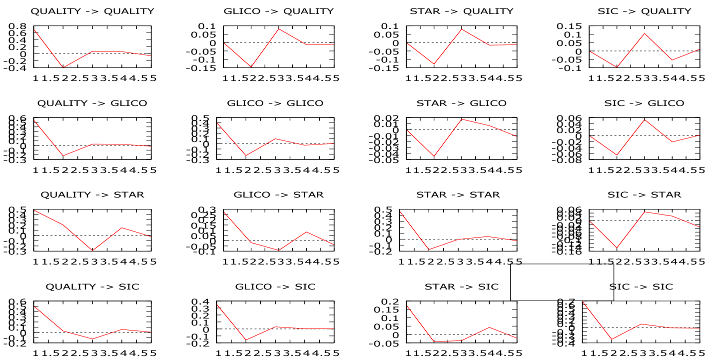

Figure 3: Impulse Response Function

The forecast error variance decomposition analysis was used to ascertain the percentage of error variance of the growth rates accounted for by each variable. From Table 9, Quality Life Assurance explained 100% of the error by its own innovations with the rest of the companies explaining none (0%) in the first period. At period 5, 89.89% of the error variance was explained by itself and with 3.81%, 3.13% and 3.18% explained by Glico Life Insurance, Star Life Insurance and SIC Life Insurance respectively. This is supported by the VAR (1) model and the Granger Causality that the growth rate of Quality Life Assurance depends on its own past innovations.

Period	Std. error	Quality Life Assurance	Glico Life Insurance	Star Life Insurance	SIC Life Insurance
1	0.703	100.000	0.000	0.000	0.000
2	0.837	93.276	3.021	2.344	1.359
3	0.854	90.246	3.823	3.127	2.359
4	0.858	89.887	3.808	3.129	2.804
5	0.861	89.878	3.812	3.134	3.175

Table 10: Decomposition of Variance for Quality Life Assurance

In period one, Glico Life Insurance explained 64.39% of its own variance innovation and with 35.61% by Quality Life Assurance as shown in Table 10. Quality Life Assurance, Star Life Insurance and SIC Life Insurance explained the forecast error variance in Glico Life Insurance by 38.60%, 0.42% and 1.30% respectively with 59.67% explained by its own innovation in the fifth period.

Period	Std. error	Quality Life Assurance	Glico Life Insurance	Star Life Insurance	SIC Life Insurance
1	0.678	35.611	64.389	0.000	0.000
2	0.753	37.913	60.978	0.354	0.755
3	0.761	38.621	59.753	0.398	1.229
4	0.763	38.628	59.665	0.404	1.303
5	0.763	38.602	59.669	0.426	1.302

Table 11: Decomposition of Variance for Glico Life Insurance

From Table 10, apart from Star Life Insurance which explained more than half of its own error variance for all the periods, quality life assurance explained much of the FEV for these periods as shown in Table 11. This indicates that the growth rate of Star Life Insurance was accelerated by its own past values.

Period	Std. error	Quality Life Assurance	Glico Life Insurance	Star Life Insurance	SIC Life Insurance
1	0.7300	34.0666	14.3873	51.5461	0.0000
2	0.7902	30.1199	12.3338	54.2846	3.2616
3	0.8480	29.9857	11.8943	54.9882	3.1318
4	0.8661	33.7880	12.3297	50.8028	3.0795
5	0.8683	33.5994	12.4702	50.7168	3.2136

Table 12: Decomposition of Variance for Star Life Insurance

For instance for period 5, 55.482% of the FEV is explained by SIC life insurance, 26.449% by quality life assurance, 14.577% by Glico and 3.492% by Star. This shows that the number of clients for SIC depends much on its own past values.

Period	Std. error	Quality Life Assurance	Glico Life Insurance	Star Life Insurance	SIC Life Insurance
1	0.941	28.839	14.168	3.484	53.509
2	1.003	25.432	14.957	3.249	56.363
3	1.016	26.281	14.658	3.290	55.772
4	1.019	26.464	14.587	3.450	55.500
5	1.019	26.449	14.577	3.492	55.482

Table 13: Decomposition of Variance for SIC Life Insurance

IV. CONCLUSION

This paper examined the relationship between Life insurance demands or the growth rates (number insured) among four life insurance companies in the Upper East Region of Ghana. The study revealed that, most of the populace in the Upper East Region of Ghana are risk averse and would therefore purchase life products in case of any uncertainty pertaining to retirement or death. It was realized that, there exist an independent relationship between the growth rates of the insurance companies. And that the number of insured for one insurance company depended directly on its own past innovations. Also the previous number insured had a significant impact on the future number insured for each of the insurance company and that there was no association between insurance companies in terms of the number purchasing these life products. Also the Life insurance penetration in the Region kept growing every year. This study suggest that insurers (i.e. the four insurance companies) should improve upon their marketing strategies to create competition among themselves.

REFERENCES

[1] Browne, M. J., and Kim, K., (1993).An international analysis of life insurance demand, *Journal of Risk and Insurance*, 60: 616-634.

[2] Burnett, J. J., and Palmer, B. A., (1984). Examining Life Insurance Ownership ThroughDemographic and Psychographic Characteristics, *Journal of Risk and Insurance*, 51: 453-467.

[3] Campbell, R. A., (1980). The Demand for Life Insurance: An Application of the Economics of Uncertainty, *Journal of Finance*, 35: 1155-1172.

[4] Enz, R., (2000). The S-curve relationship between per-capital income and insurance penetration *Geneva Papers on Risk and Insurance*, 25: 396-406.

[5] Hakansson, N. H., (1969). Optimal Investment and Consumption Strategies Under Risk, Uncertain Lifetime and Insurance, *International Economic Review*, 10: 443-466.

[6] Kunreuther, H., and Pauly, M., (2004). Neglecting disaster: why don't people insure against large losses. *Journal of Risk and Uncertainty*, 28:5-21.

[7] Mossin, J., (1969). Aspects of rational insurance purchasing, *Journal of Political Economy*, 79: 553-568.

[8] Yaari, M. E., (1965). Uncertain lifetime, life insurance, and the theory of the consumer.*Review of Economic Studies*, 32: 137-150.

[9] Zietz, E., (2003). An Examination of the Demand for Life Insurance, *Risk Management and Insurance Review*, 6: 159-192.