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Stochastic Risk Volatility Forecasting in Poultry Agribusiness in Delta State, Nigeria

[a]ACHOJA Felix Odemero*, [a]OKOH Rosemary Ngozi

[a]Department of Agricultural Economics and Extension, Delta state University, Asaba Campus, Nigeria.
*Corresponding author: lixmero40@yahoo.com

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Abstract

The dearth of information on financial risk has negative effect on the growth of poultry agribusiness. The purpose of the study was to determine the mean financial risk volatility in poultry agribusiness in Delta state, Nigeria. Six years panel data (2004 – 2009) were collected from 200 poultry farms using structured questionnaire. Collected data were analyzed using $ARCH_{(5,5)}$ Model and Time Response Model. Test of hypothesis using Durbin Watson statistics indicated that there is no volatility clustering of financial returns. The result of ARCH model showed a random walk (i.e. upward and downward swings) of standard error of financial risk with a mean volatility of 7.5% in poultry agribusiness over the 6 years period. Time Response prediction model gave an impression that short run forecast of financial risk volatility in poultry agribusiness is feasible. The study recommends early warning / early mitigate for measures of the short run to manage financial risk in poultry industry.

Keywords: Financial, Risk, Volatility, Forecasting, Poultry, Enterprise

Introduction

Delta State is one of the producers of farm-raised broilers in Nigeria. However, Goodwin *et al.,* (2005) reported that broiler production over the world has been characterized by fluctuations in annual total output levels for the last ten years. This has brought significant reductions in the number of broiler farms and negatively affected the finances of broiler farmers and income of producers. This has translated to instability of broiler markets in terms of fluctuating input and output prices. The ultimate effect of this is that producers and potential investors are getting discouraged. As a result, many of the existing poultry farms are folding up and prospective investors are becoming increasingly skeptical to invest (Aihonus, 1999). This situation threatens the survival and growth of the industry. There is therefore the need for concerted efforts to save the poultry industry from total collapse (Bamire, *et al.*, 2009) through financial risk volatility forecast. In this study, financial risk is defined as the probability of financial loss in poultry business. It is the uncertainty in financial returns in poultry industry. Successful volatility forecast is expected to bring progress to the poultry industry in Nigeria that is capitalized by as much as 2 trillion and employs no fewer than 30 million Nigerians on the whole (FAOSTAT, 2006).

Estimation of financial risk in broiler poultry will require information on the trend in returns to investors' over time and space. Persons considering either entering the broiler business or seeking to expand existing operations require information on the financial risk level. Lending institutions require such information in evaluation of loan application for establishment and expansion of broiler poultry business. Failure in volatility forecasting could lead to blind investment in the enterprise. Financial risk is missing variable in poultry farm plans as investors based their risk fears on intuitive knowledge, educated guess work (guess estimate) and sheer speculations without empirical facts on financial risk in poultry enterprises. Hence accurate forecasting of risk volatility will boost the confidence level of investors, insurance agents and researchers seeking to understand financial indices in the broiler sub-sector of the economy. Nigeria's plans to attain the Millennium Development Goals (MDGs) of poverty and hunger reduction in 2015 and become one of the world's leading economies in the year 20-20-20, requires that financial risk volatility forecast be encapsulated in the projection of national development plan for broiler production.

The purpose of this study was to evaluate volatility forecasting measures and determine mean financial risk volatility in broiler poultry agribusiness (2004 - 2009) in Delta State, Nigeria.

Theoretical Framework

Accurate forecasting of economic indexes is of vital interest to traders, investors, risk managers as well as researchers and policy makers seeking to understand market dynamics. As it is well known, economic indexes are used to form forecasting models. Although theoretically, forecasting should reflect all available information, including time-series information, evidence is mixed on which forecasting model performs better. Forecasting requires estimation and prediction though they are used interchangeably. The objective of forecasting centers on the determination of future value or event. In business organization, whether big or small, forecasting is an important tool for predicting a trend of business activities e.g. sales forecasting, profit forecasting, output forecasting and price forecasting (Ekanem and Iyoha, 2003). Often, forecasting methods include regression analysis, econometric forecasting, co-integration and error correction model.

The forecasting of risk is the ultimate test of good farm planning. It has been reported by Erickson and Downey (1987) that the ability to determine what the future holds is the highest form of farm management skill. Risk forecasting is the logical extension of risk analysis into a future time setting. Many failures in risk prediction tend to result from ambiguous and generalized guess works of analysts. Forecasting risk is never a guessing game, rather it is based on empirical approach to farm planning. Often forecasting models are hinged on different forms of regression analysis.

Duer (1993), identified four forms of forecasting model, viz judgment model, projection model, leading variables model and coincident – variables model. These four model forms are not mutually exclusive. Elements of two or more may be present in a single prediction model. Any of the models can contain stochastic (probabilistic) elements. The projection and leading variables models are commonly used. The projection model derives a forecast magnitude from the base period. The gap between the base period and the target period classifies the projection into either short-term or long-term. Projections are estimates for the future under assumed conditions (Duer, 1993).

The leading – variables model is exemplified as:

$$V_n = g\,(a_o,\ b_o,\ \text{--------}\ y_o,\ z_o) \qquad (1)$$

where a_o, b_o, up to z_o are values, in a base period, of variables that are thought to have certain relationships (g) to the forecast variable 'v' at the time 'n'. The magnitude to behaviour of 'v' at a given time is thought to the related to be magnitude or behaviour of the other variables at an earlier time. The other variables are thought to lead 'v' so that by keeping an eye on them the forecaster can use them as predictor of 'v'. That notwithstanding, the leading – variables model is best suited to short term forecasting because in a dynamic economy no manageable set of variables can be found that will predict the state of another variable very far ahead. Duer (1993) had earlier expressed the caveat that too much can transpire to mar or break a long-term relationship established by a model. Duer (1993) concluded his thesis by asserting that a good forecast is one that fulfills its purpose, and the purpose of a good forecast is to arouse people to a possible risk (danger). If they respond by adopting proper management strategies, the risk (danger) is averted, and the forecast would not come true. Yet it was a good forecast.

Using regression model in forecasting requires more detailed a priori assumptions than correlation analysis. In this case, an explicit functional relationship between a dependent variable and one or more independent variables is hypothesized. A statistical technique is then used to fit the equation to empirical data for the purpose of estimation or prediction. For the estimated relationship and forecast of values for the independent variables, values of the dependent variables can be estimated. The regression equation is usually linear, semi-log or double-log.

The linear regression model is always of the form;

$$Y = \alpha + \beta X_i + \varepsilon_i \qquad (2)$$

Where:

Y = dependent variable

X = the explanatory or independent variables;

α, β = unknown regression parameters; and

ε_i = stochastic disturbance term

The GARCH (1,1) model assumes that the log-return at time t, R_t is normally distributed with mean and variance, V_t, and that V_t follows the process:

$$V_{t+1}=\alpha_0+\alpha_1 r^2_t+\beta_{Vt} \quad (3)$$

Since

$V_t=\alpha_0+\alpha_1 r^2_t+\beta_{Vt},\ V_{t+1=}\ (\alpha_{0+}\beta\alpha_0)+\alpha_1 r^2_t+\beta\alpha_1 r^2_{t-1}+\beta^2 V_{t-1}$
(4)

and successive substitution back to time t_{-j} yields the alternative expression of the GARCH (1,1) model:

For this purpose, what is of interest is not the forecast volatility at a future point in time but the forecast volatility over the future period from t to t_{+s}. This forecast, which is label 'GARCH' is an average measure of the volatility expected each period from t to t_{+s}.

Modeling of risk volatility would require estimating the distribution of variance of rate of returns over time (i.e. Historical, panel or time series variance of rate of returns). So many authors have adopted this approach involving time series model such as ARCH, GARCH, EGARCH, Historical Mean Absolute Deviation (HMAD), Historical Standard Deviation (HSD), chow test and regression model to forecast the volatility of economic indices such as inflation rate, exchange rate, unemployment rates (Bollerslev, 1986) and rate of returns. Autoregressive conditional heteroscedasticity (ARCH) model was developed by Engle (1982) and the generalized autoregressive conditional heteroscedasticity (GARCH) model was proposed by Bollerslev (1986). Engle (1982) maintained that in econometrics, an auto-regressive conditional heteroscedasticity model (ARCH) considers the variance of the current error term to be a function of variance of the previous time periods error terms. ARCH relates the error variance to the square of the previous period's error. It is employed in modeling financial time series that exhibit time-varying volatility clustering, i.e., period of swings followed by periods of relative calm (random walk).

Materials and Methods

Study Area, Sample Size and Sampling Technique

This area was chosen for this study due to the substantial presence of commercial broiler enterprises. The state has a total population of about 4,098,391 people according to 2006 National Population Census. It comprises 25 Local Government Areas (L.G.As).

The Population of the Study is includes all broiler farmers in Delta State, Nigeria. To avoid selectivity bias, a chance – mechanism was employed to select the sample for the study. Hence the overall sample size was obtained using Yamane's formula (1973). This is shown below:

$$n= N/1+ N\ (e)^{\%} \quad (5)$$

Where:

n = sample size (to the nearest whole number)

N = sample frame

e = tolerable error term or error margin or confidence level (usually at 5%).

With this formula, one was 95% confident that the sample was a true representative of the population. However, the **Bowler's formula,** as adopted by Umebali (2005), was used to obtain the sample size in each of three agro-ecological zones (stratum) in the study area. The Bowler's formula is shown below:

$$\mathbf{nh} = \eta N h/N \quad (6)$$

Where:

nh = number of farms sampled from each stratum (agro-ecological zone) (70)

η = sample size (210)

N*h* = mean number of items in each stratum (165)

N = sample frame (496)

To avoid selectivity bias the sample for the study was obtained using probabilistic and non-probabilistic methods. Probabilistic technique (multi-stage random technique) was considered appropriate because with this method, every agricultural zone, L.G.As and every commercial broiler farmer (i.e. every member of the population) in the study area had equal chance of being selected for the study. The multi-stage sampling method implies that a representative unit (the sample) is composed in a step-wise manner (stages). The procedure for multi-stage sampling technique that was adopted in the study is as follows:

Stage 1: Selection of L.G.As

Five L.G.As were randomly selected from the list of the L.G.As in each of the three agricultural zones. This gave a total of 15 L.G.As out of the 25

L.G.As. This gave 60% of the total L.G.AS that were captured in the study. These were Oshimilli North, Oshimilli South, Ika North, Ika South, Ndokwa West, Ethiope East, Udu, Uvwie, Ughelli North, Sapele, Isoko North, Isoko South, Patani and Warri North.

Stage 2: Selection of Farms

In each of the 15 selected L.G.As, 15 broiler farms were selected. Only farms that were registered with the Ministry of Commerce and Industry in Delta State were chosen. It was assumed that registered farmers would have their farm records. Also, only farmers that have been in operation for at least five years previously were chosen for the study. This gave a total of 210 broiler farmers that were selected and studied.

Data Collection Mechanism

Data gathering mechanism (DGM) adopted in the study followed the techniques described below: Time Series data were collected from respondent farmers over a period of six years (2004 – 2009). Best forecast results are generally obtained using historical data. There is no clear 'best' length of period. Valderama and Engle (1999) made use of a three year historical data in their study. Akanni and Akinleye (2004) made use of eight year historical data in their analysis. Ahmad *et al* (2005) made use of 19 years regional annual data. Time Series was considered appropriate for this study for the following reasons:

- it gives more informative data, more variability, less collinearity among variables, more degree of freedom and more efficiency (Chamberlain, 1984); and
- by studying the repeated cross-sections of observations, time series data are better suited to study the dynamics of volatility (Gujarati, 2006).

In this study, since risk was based on variability, time series data become more appropriate. Based on historical data regarding risk, it is possible to develop some forecast for the future. Structured questionnaire was the main instrument used for data collection. One set of questionnaires was constructed, validated and used for the study. It was tagged broiler enterprise questionnaire. Secondary data were also collected from bulletins and government publication (CBN and FOS Annual Reports). Data were collected from 210 respondents, but 200 copies were correctly filled by the respondents, hence respondents' response performance was 95%. Historical data were collected on the farms' financial statement, yield, prices of inputs and output, farm enterprise budget, and bank interest rates for the past six years (2004-2009). Information was also collected on factors that determine risk in broiler enterprise.

Measurement of Risk Parameters

Farm Risk Level

This was measured by the standard deviation of net profit of individual broiler farms over six year duration.

Financial Risk Level

This was determined by computing the mean risk level for each year and then determining the standard deviation of net profit for the six years.

Risk Estimators

Variance, standard deviation and mean absolute deviation of net return have been used as risk estimators, but standard deviation of net profit was chosen as the key risk estimator due to its advantage over the other estimators.

Risk Volatility

This is a measure of the degree of change of financial risk from time to time (2004 – 2009). The yearly standard error of financial risk as reflected in ARCH and GARCH variance models, was used to estimate financial risk volatility in the study.

Techniques for Data Analysis

The historical standard deviation of net profit was used parametrically as risk estimator.

$$\textit{Historical variance (V-ROI)} = \sum_{J=1}^{n} \frac{r^2_{t-j}}{n} \qquad (7)$$

Where:

$r_{t-j} = R_{t-j} - \mu$ $\quad r_{t-j}$ = Historical net Return

μ = Mean net Return
n = Number of years

The square root of variance was used as the standard deviation of return on investment.

Financial Risk Volatility Forecasting in Commercial Broiler Enterprise

Stochastic variables such as risk often exhibit the phenomenon of volatility. The knowledge of volatility and variability in the rate of returns to investors over time is of crucial importance in the field of economic analysis. High variability or volatility of rate of returns could mean greater uncertainty and risk. This makes financial planning difficult. Financial risk volatility forecasting in broiler enterprise was achieved using the

The following hypotheses were formulated and tested to guide the study:

H_0: *There is no significant risk volatility clustering in broiler enterprise (2004 – 2009).*

H_1: *There is significant volatility clustering in broiler enterprise (2004 – 2009)*

H_0: *The yearly financial risk values (2004 – 2009) are not significantly higher than zero*

H_1: The yearly financial risk values (2004 – 2009) are significantly higher than zero

ARCH model and Time Response model.

Estimation of ARCH model starts with Auto Regression (AR) model as shown below:

AR-Model

$$\mu_t = \beta_0 + \beta_i \o^2_{t-1} \quad (8)$$

Step I

Estimate the $AR(_P)$ model

$$ROI_t = \beta_0 + \beta_1 ROI_{t-1} + \ldots + \beta_p ROI_{t-p} + \mu_t \quad (9)$$

Step II

$$\mu^2_t = \beta_0 + \beta_1 \mu_{t-1} + \ldots + \beta_p \mu^2_{t-p} \quad (10)$$

$ARCH_{(P)}$ model is explicitly specified as:

$$\o^2_t = \beta_0 + \beta_1 \o^2_{t-1} + \beta_2 \o^2_{t-2} + \beta_3 \o^2_{t-3} + \ldots \beta_p \o^2_{t-p} + \mu_t$$

(Gujarati, 2002) (11)

Where:

$\o^2_t$ = Mean adjusted relative to change in risk;

$\hat{a}_0$= Intercept term;

$\hat{a}_1 - \hat{a}_P$ = Coefficient of $\o^2_t$ from time t_{-1} to P.;

P = Number of autoregressive terms; and

μ_t= White noise term.

ARCH Model Specification

An ARCH(q) model can be estimated by OLS. Lagrange multiplier test is used to determine lag length. There are several steps involved in the estimation.

Step I: Estimate the best fitting AR(q) model

$$y_t = \alpha_0 + \alpha_i y_{t-i} + \ldots + \alpha_q Y_{t-q} + U_t \quad (12)$$

$$Ut = \alpha_0 + \sum_{i=1}^{q} \alpha_i y_{t-i} + U_t - \alpha \quad (13)$$

where

y_t= ROI for broiler;

y_{t-i}= are lagged values of y_t

α_0 = Positive constant term;

α_i = Coefficients of lagged values of y_t;

q= Number of lags; and

U_t = error term denotes return (or residuals net of a mean process)

Step 2: Obtain the squares of the error term $U_t^2$and regress them on a constant and q lagged values of U^2_t as follows:

$$U_t^2 = \alpha_0 \sum_{i=1}^{q} \alpha_i \; U^2_{t-i} \quad (14)$$

Where

α_0 = Positive constant, and

q = Length of ARCH lags

Step 3: Test Hypothesis

H_0: $\alpha_i = 0$,$\alpha_i \neq 0$ The H_0 test is a test of no ARCH components. $\alpha_i = 0$ for *i=1, ;q*.

H_i is test of presence of ARCH components. In the sample of T residuals under the H_0 of no ARCH errors, the test statistics follows a X^2 distribution with q degrees of freedom. If $TR^2 >$ the X^2 tab value, the null hypothesis is rejected and conclusion is that there is an ARCH effect in the autoregressive moving average ARMA model. If $TR^2 < X^2$ tab value, H_0 is accepted, that is, there is no ARCH effect. If ARCH is present then one assumes an auto regressive moving average, ARMA, model for the error variance (Bollerslev, 1986).

Correlated error variance over time indicates a phenomenon of risk volatility clustering. Test of significance was achieved by Durbin-Watson *d*. The $ARCH_{55}$ model was analyzed using software packages (E-view and Micro fit). In this study, ARCH model was adopted in forecasting risk volatility in commercial broiler industry.

Results and Discussion

Forecasting Measures of Financial Risk Volatility in Broiler Agribusiness

Volatility forecasting of financial risk in broiler industry was achieved using the autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models. The essence was to test the hypothesis of the existence of volatility clustering of risk parameters over the six year period.

Testing of Hypothesis 3

H_0: There is no significant volatility clustering of risk parameters coefficients, that is, there is no significant autocorrelation between the coefficients of variance of financial risk parameters for the period,

i.e. $\beta_t = \beta_{t-1} = \beta_{t-2} = \beta_{t-3} = \beta_{t-4} = \beta_{t-5}$

The result of the ARCH model is presented in Tables 1. Volatility forecasting model selection criteria was achieved using the different test-statistics viz: R^2, Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Durbin-Watson (D.W) statistics. This was done to evaluate the forecasting performance of ARCH and GARCH models. Table 2.0 shows volatility forecasting model selection criteria.

Table 1. ARCH volatility forecasting model

	Coefficient	Std. Error	Z-Statistic
C	0.00075	0.001176	0.642715
C_2	0.000173	0.000414	4.170772
C_3	0.275949	0.240839	1.145783
C_4	0.368957	0.043017	8.577084
C_5	-0.606742	0.000817	-742.5604
C_6	0.033333	0.201731	0.165236

The absolute low values of Akaike information criterion (AIC) and Schwarz information criterion (SIC) for the ARCH model compared to its counterpart GARCH values indicated that ARCH outperformed GARCH. All the relevant model selection criteria indicated that the ARCH model performed better than the GARCH in forecasting the financial risk volatility clustering. As a result, the ARCH model was adopted for the study. Oduh *et al* (2009) has earlier maintained that the validity and efficiency of a forecast model depend on its output which is determined by certain econometric assumptions and tests.

Using yearly standard error of financial risk as a measure of financial returns volatility, the mean yearly volatility was determined to be 0.0748 (7.5%). The absence of volatility clustering is an indication that there is a sharp financial risk volatility shock in the broiler industry in Delta State. So much so that high returns in previous period do not necessary translate to expected high return in the future period. It also follows that financial failure in the previous period does not necessarily translate to failure (loss) in future period. In most cases the reverse is the case. This is in agreement with cobweb theory which is often applied in describing the fluctuations/ dynamisms in agricultural industry (Ord and Livingstone, 1976).

Table 2. Volatility forecasting model selection criteria

Test statistics	ARCH model	GARCH model
R^2	10%	6%
Akaike	-6.17	-6.69
Schwarz	-6.03	-6.45
Durbin Watson	1.91	2.19
	Residual model	Residual model
R^2	0.7%	0.2%
Akaike	3.18	4.68
Schwarz	3.21	4.72
Durbin Watson	2.00	1.99

Mean Financial Risk Volatility in Broiler Poultry Agribusiness

The $ARCH_{(5,5)}$ estimated equation is presented as:

$$Øt = 0.00075 + 0.000173C_2 + 0.2759C_3 + 0.3689C_4 + 0.6067C_5 + 0.0333C_6 \quad (15)$$

t = (0.6427) (4.1707) (1.1457) (8.5770) (742.56) (0.1652)

S.E. = (0.001176) > (0.00004) < (0.2408) > (0.0430) > (0.0008) < (0.2017)

Trend Forecasting of Financial Risk Volatility using ARCH Variance Equation

In this study, attempt was made to forecast the financial risk volatility in broiler enterprise over the period 2004 – 2009, under review in Delta State. To achieve this, the linear regression of the yearly standard error of ARCH variance model was estimated. In this case, standard error was used as an estimate of financial risk volatility (the dependent variable and corresponding years the exogenous variables). The emanating prediction equation is given as:

$$R_{t+1} = 0.514 + 0.155Yr \quad (16)$$

Trend Forecasting of Financial Risk Volatility is shown in table 3.

Financial Risk Volatility Projection for 2009, 2010, 2015 and 2020

The financial risk projections for the broiler enterprise in Delta State for 2009, 2010, 2015 and 2020 is presented below: The forecast equation adopted is given as:

$$R_{t+1} = 0.514 + 0.155Yr \quad (17)$$

Table 3. Trend forecasting of financial risk volatility

S/N	Year	Actual	Unadjusted forecast	Adjustment factor	Adjusted forecast
1.	2004	0.0004	0.0514+0.155(1)=0.2064	0.2%	0.0413
2.	2005	0.2408	0.0514+0.155(2)=0.3614	0.7%	0.2529
3.	2006	0.0430	0.0514+0.155(3)=0.5164	0.08%	0.0413
4.	2007	0.0008	0.0514+0.155(4)=0.6714	0.12%	0.0805
5.	2008	0.2017	0.0514+0.155(5)=0.8264	0.24%	0.1983
Hence average adjustment factor = 1.34/5 = 0.27%					

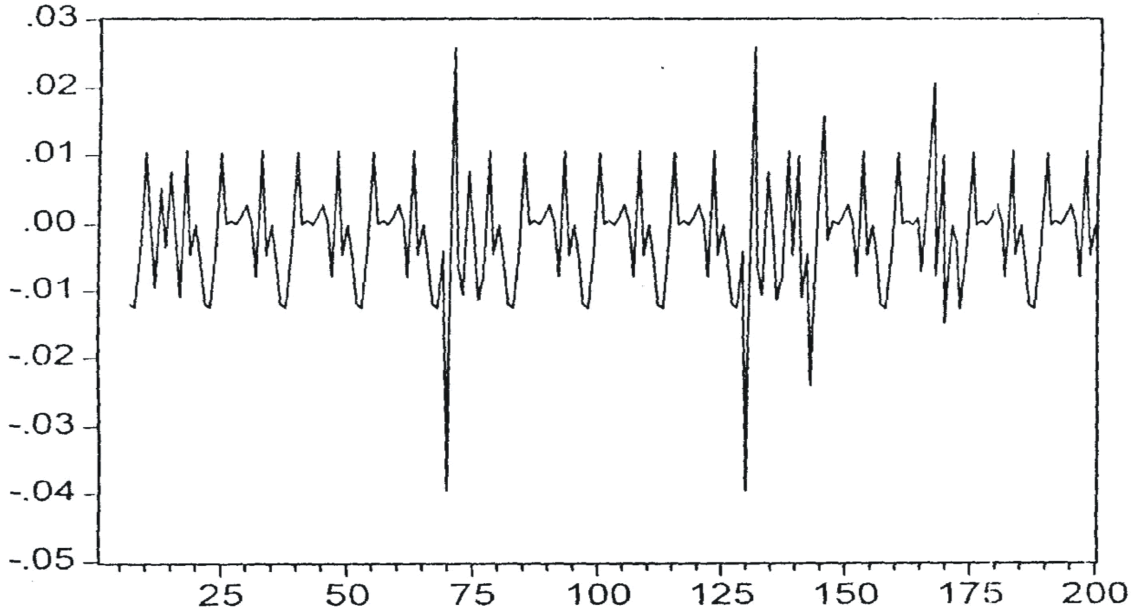

Figure 1. Conditional variance or volatility for ARCH estimate showing the pattern of financial risk volatility across periods

Future trend forecast of risk volatility is shown in table 4.0. Based on the minimization of the sum of squared errors forecast in this case, it appeared that the data justified a trend forecast with an adjustment factor of 0.27%. This highlighted the importance of using prediction equation to make inference within a relevant and reasonable range of values. Financial risk forecast for 2009 and 2010 were instances for short term risk prediction with reference to the base year of study, while the financial risk forecast for 2015 (millennium development target year) and 2020 (Nigeria economic development target goal year), were instances of medium and long term financial risk forecast, respectively.

The result indicated that the longer the projection year, the higher the forecast risk value, all other factors that affect financial risk remaining constant. This is because the distant future is more cloudy and uncertain than the near future.

A further noteworthy finding of the study for both ARCH and GARCH was that the standard errors of forecast exhibited irregular pattern in between the preceding and succeeding years. This suggested that forecasting into the distant future might be hazardous in the broiler enterprise. This is in agreement with the caveat earlier expressed by Gujarati (2003) with respect to dynamic forecasts. Short term/static forecast will therefore perform better in financial risk forecasting than long term forecast in broiler enterprise in Delta State, Nigeria. The solution to this is to apply risk forecast adjustment procedure. Hence, by adopting risk adjustment factor, financial risk volatility forecast can be made more realistic.

This specification is often expected in a financial context, where a producer is interested in the trend of volatility (variance) by forming a future picture. This is achieved by forecasting future variance in return from previous period return (i.e. volatility observed in the previous period). This is only possible where there is evidence of volatility clustering (serial correlation of variances and residual terms). If this happens the residual terms (U_{ts}) will be bunched together (cluster) and their difference will be small such that risks gradually cancelled out. It follows that if return variance was unexpectedly large in either the upward or the downward direction, then there is need to increase the estimate of the variance for the future period. Volatility clustering is often common with financial returns in manufacturing industry, where large changes in returns are likely to be followed by further large variation in the future. The results of this study suggest that agricultural industry is different from manufacturing industry since volatility clustering was not observed. All stochastic volatility models have some levels of forecasting power. To that extent, the ARCH is a good forecasting model because it has no bias (the constant is statistically insignificant from zero).

The ARCH model revealed that the standard errors of forecast for the proceeding and succeeding years were at random. This is indicative of a random walk (RW) (continuous cycles of low and high values) of the financial risk estimator for the six year period. This further buttresses widespread volatility shock in the poultry industry. This negates the report of Ederinton and Guan (2000) who observed that in financial data, large changes in returns are likely to be followed by further large changes. This result of this study suggests that forecasting into the distant future may be difficult and hazardous. This is in agreement with the caveat earlier expressed by Gujarati (2003) with respect to dynamic forecasts. Dynamic forecast of financial risk volatility is difficult in the broiler poultry enterprise. Static (short term) forecast is rather feasible and advisable.

The result of this study on financial risk volatility is rather unique to the broiler enterprise. The random shock observed in the study could possibly be attributed to the many reasons. In 2005, the threat of the incidence of avian flu introduced a major distortion into the broiler industry in Delta State, Nigeria. As a result, there was high loss of income due to low demand for matured broiler. This ugly experience brought about low aggregate investment in 2006. Input prices were also low due to fall in demand for poultry inputs. The relatively low output attracted high price due to scarcity of the product. This is in line with economic theory. As a result, revenue and return on investment for the few investors increased. The relatively high output price and returns in the previous year (2006), motivated increased aggregate investment in broiler production with an expectation of high returns. The expanded investment in the industry resulted in a glut. As a result, price of matured broiler fell. Revenue and return on investment also dropped accordingly. The situation of random walk followed suit in 2008 and 2009 production cycles.

The result of the study goes to confirm the fluctuations (volatility) in the prices of inputs and output as well as rate of return in commercial broiler production in the study area. Many studies (Parkinson, 1980; Garman and Klass, 1980; Taylor, 1982; Beckers, 1983; and Hull and White, 1987) estimated volatility of price and rate of returns. They had common conclusion that product price and returns volatility forecasting were very useful in evaluating investment possibilities. To that extent, volatility estimate becomes a natural estimate of true risk distortion. This is capable of boosting or otherwise the confidence of investors and stakeholders in broiler poultry enterprise in the study area.

Table 4. Future trend forecast of risk volatility

Year	Unadjusted forecast	Adjusted forecast
2009 Yr(6)	0.914	0.265
2010 Yr(7)	1.1364	0.306
2015 Yr(12)	1.91	0.516
2020 Yr(17)	2.686	0.725

Conclusion

Variability in profitability and greater uncertainty in cash flows can make profit forecasting and financial planning difficult. It was this concern that called for this investigation. Available empirical evidence from the study confirmed the fact that financial risk cut across the surveyed farms. Long term (dynamic) forecasting of financial risk in the broiler industry is difficult without the use of adjustment factor since there is no volatility clustering on the basis of information provided by the ARCH model. The study provides information on mean Random Walk (RW) of 7.5%. This could help broiler farmers to accommodate risk in their short term farm planning. It was explicitly established in the study that without early action, financial risk volatility could have adverse effect on the growth of the industry in the long-run. Knowledge and consciousness of financial risk, based on investors experiences, will translate to the cultivation of efficient risk management skills among broiler producers in Delta State, Nigeria. The essence of risk forecasting is to arouse broiler producers of a possible financial failure in the future. If producers respond by Early-Warning/Early-Action risk mitigation strategies, the failure could be averted.

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