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RESEARCH ARTICLE

MODELING CORN RETURNSVOLATILITY WITH SEASONAL SHIFTS

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ABSTRACT

The paper investigates the best fit estimation technique for modeling returns and volatility of corn. It further estimates the pass-through effects of volatility risks to corn returns. It provides two main innovations: first, it analyzes corn returns volatility types namely idiosyncratic and systematic volatility types using the Narayan and Popp (2010) test and further modified the estimations to include both symmetric and asymmetric volatility models. Second, it uses the Kalman filtering process to estimate the pass-through effects of volatility risks to returns of corn. The paper finds two structural breaks that occur in 2015/2016 and 2018. It notices the existence of persistence and leverage effects in the returns volatility of corn and that rising volatility regardless of types, necessitates demand for higher returns by investors to hold corn investment. Conclusively, it recommends that, when modeling corn return volatility, issues of asymmetric effects and structural shifts are extremely pertinent and that investors should structure investment portfolio with more of idiosyncratic volatility corn prices to maintain stable returns.

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INTRODUCTION

A clear understanding of the presence of volatility risk in grain prices particularly, corn prices is crucial to help design a sustainable strategy to hedge against the attendance effect emanating from volatility risks and associated to sharp spike in prices of grains and other commodities. Studies have documented several factors that could be accountable for price increases; these include: ban of export of major grain such as corn, supply shortages, reduced stock-to-use ratios and panic buying by some major importers (Gilbert, 2010; and Minot, 2014). The long shift (decline) in the prices of corn between 2017 and 2019 with increased volatilities of prices have generated immense concerned for investors to searching for alternative way to manage these lingering risks. Having a better comprehension on effective modeling of price returns and volatility becomes imperative considering seasonal shifts in price trends. It is obvious that this is not the first time that there is going to be a shift in commodity prices, specifically prices of grains. For instance, commodity prices rose rapidly between 2010 and 2011; and since 2007 global grain markets have witnessed an upward shift in price volatility. This is evident in the submission of Minot (2014. which provide analyses of pre-during-post of the global crises. The study shows that for these periods the unconditional volatility of grain prices rose by 52% for corn, 87% for rice ad 102% for wheat, respectfully. However, the recent shift was a downward trend and necessitates careful examination. The paper therefore, contributes to the existing studies on commodity price volatility modelling in three folds: first, it uses the recent Narayan and Popp (2010) to model the corn return volatility. The approach allows for structural breaks in data series. Second, the corn return volatility analysis was performed using the volatility sources. This is an improvement to existing studies on emerging markets that had concentrated on single source of volatility. Third, the paper considers both systematic and idiosyncratic volatility risks models. The main thrust of the paper is to identify structural breaks that occur in corn priceand price returns; and consequently, show how the structural events affect the returns of investors in corn. Our results also lend support for the consideration of pass-through effects when modeling corn return volatility. Comparatively the idiosyncratic volatility models seem more appropriate in modeling corn return volatility than the systematic ones. Most importantly, the Exponential GARCH (EGARCH) model gives the best fit and therefore, propose that when modeling corn return volatility the EGARCH model should be considered. Meanwhile, the effects of corn volatility risks on corn returns remain positive. The implication therefore, is that investors in corn should expect higher returns during rising volatility regardless of types and otherwise. The rest of the paper is structured as follows. Section two present data, methods and relevant preliminary estimates. Section three describes the analysis of empirical results and section four concludes the paper.

DATA AND METHODS

The weekly corn price data used in this study are garnered from the Bloomberg terminal over the period of January 2014 and April 2019. The pre-estimation analysis is conducted in two folds: the first provides descriptive statistics for corn returns volatility considering the two types of volatilities generated –systematic and idiosyncratic volatilities; the second shows the unit root test using the NP unit root test with structural breaks. The corn returns is computed with the formula $\left[\ln(P_t)/\ln(P_{t-1})*100\right]$. The systematic volatility series are obtained from the monthly standard deviation of corn returns $[\sigma]$ and the idiosyncratic volatility series are generated from the monthly standard deviation of the residual of the first-order Autoregressive (AR(1)) model of the form $\left[r_t^i = \vartheta_0 + \vartheta_1 r_{t-1}^i + \varepsilon_t^i\right]$. Table 1 presents the descriptive results on corn return volatility for both systematic and idiosyncratic volatilities. It seems evidence from the results that there are significant variations in the trends of the two volatilities. Comparatively, following the standard deviation result, the trend of the idiosyncratic volatility appears more volatile than the systematic volatility. The statistical distribution of the series, indicates that both idiosyncratic and systematic volatilities are negatively skewed which shows that there exist extreme right tails in both series. Other descriptive statistics show that corn return volatility series are leptokurtic (both possess fat tails than the normal distribution); the Jarque Bera statistic reveals evidence of non-normality for both systematic and idiosyncratic volatilities. Since the descriptive results show that corn return volatilities are negatively skewed and not normally distributed, therefore, the inferential statistics that is most appropriate must follow non-normal distributions (see Wilhelmsson, 2006). The alternatives available consist of the generalized error distribution (GED. the Student-t distribution, the Student-t distribution with fixed degree of freedom and GED with fixed parameter. All these non-normality procedures are conducted for each of the volatility models and the model selection criteria are used to determine the most appropriate models. Only results that are best fit in each of the techniques is reported in the report. Results of the unit root test are presented in Table 2. The estimations follow the NP test that allows for the inclusion of two structural breaks in the series. The NP test is based on two assumptions on the deterministic components. The first allows for the two breaks in the intercept of the data series, which we tagged model 1 (M1). The second allows for two structural breaks both in levels and in slope of trend of the series. It is named model 2 (M2). Therefore, the two models are specified differently to consider for the deterministic component. The models are specified as follows:

$$d_t^{M1} = \beta_1 + \beta_2 t + \pi^*(L)\left[\phi_1 DU'_{1,t} + \phi_2 DU'_{2,t}\right] \tag{1}$$

$$d_t^{M2} = \beta_1 + \beta_2 t + \pi^*(L)\left[\phi_1 DU'_{1,t} + \phi_2 DU'_{2,t} + \varphi_1 DT'_{1,t} + \varphi_2 DT'_{2,t}\right] \tag{2}$$

Where $DU'_{i,t} = 1\left(t \succ T'_{g,i}\right); DT'_{i,t} = 1\left(t \succ T'_{g,i}\right)\left(t - T'_{g,i}\right); \quad i = 1,2.$

Also, $T'_{g,i}, i = 1,2$ denotes the true break dates. The parameters ϕ_i *and* φ_i $i = 1,2$ are the magnitude of the level and slope breaks. $\pi^*(L)$ is the polynomial lag operator that allows breaks to occur slowly over time (see Narayan *et al.,* 2010). The procedure follows the innovative outlier framework and it allows for changes to the trend to occur gradually rather than been instantaneous. The assumption behind the framework is that the series reacts to shocks from innovation process (i.e. a Moving Average representation of the shocks).

Following the assumption on the deterministic component (d_t) and stochastic component (ν_t) of σ_t^{Ri}, the reduced form of the structural model of the unit roots[1] test can be specified and estimated:

$$\sigma_t^{R(M1)} = \varphi\sigma_{t-1}^R + \beta_1 * + \beta_2 * t + \theta_1 D(T'_B)_{1,t} + \theta_2 D(T'_B)_{2,t} + \lambda_1 DU'_{1,t-1} + \lambda_2 DU'_{2,t-1} + \sum_{j=1}^{m} \alpha_j \Delta\sigma_{t-j}^R + \varepsilon_t \tag{3}$$

$$\sigma_t^{R(M2)} = \varphi\sigma_{t-1}^R + \beta_1 ** + \beta_2 * t + \theta_1 D(T'_B)_{1,t} + \theta_2 D(T'_B)_{2,t} + \lambda_1 * DU'_{1,t-1} + \lambda_2 * DU'_{2,t-1} + \rho_1 * DT'_{1,t-1} + \rho_2 * DT'_{2,t-1} + \sum_{j=1}^{m} \alpha_j \Delta\sigma_{t-j}^R + \varepsilon_t \tag{4}$$

Where $D(T'_B)_{i.t} = 1\left(t = T'_{B,i} + 1\right); i = 1,2.$ In this case, to test the unit root of null hypothesis of $\varphi = 1$ against the alternative hypothesis of $\varphi \prec 1$. The NP test suggests the use of t-statistics of $\hat{\varphi}$ obtained after equations (3) and (4) have been estimated. The break dates are selected using the sequential procedure proposed by the NP test and appropriate critical values as indicated in the work of Narayan et al (2010). In Table 2, the unit root test results are presented with the optimal break point dates for both volatility types. As presented in Table 2, the two types of return volatility series are non-stationary after accounting for structural breaks and thus, adequate cognizance should be taken to recognize these breaks when dealing with corn returns volatility modeling. Expectedly, the break dates (TB1 and TB2) for the two volatilities considered are not far apart. The first break was experienced in 2014 for both considered volatility types. Correspondingly, the second break (TB2) appears during the 2018 trading bout. In this period, the corn market witnessed tremendous negative sentiments, rising speculations and huge divestment and the volatility risks were rising against falling corn price trajectories. The Kalman filtering process was adopted to examine the pass-through effects of these volatility types on corn returns of investors. The state-space representations of the approach were specified as follows.

$$R_{i,t} = \gamma_{i,t}\sigma_{i,t} + \nu_{i,t} \tag{5}$$

$$\gamma_{i,t} = \phi_k \gamma_{i,t-1} + \upsilon_t \tag{6}$$

Equation (5) in the state-space specification is the measurement equation. While, equation (6) is the transition model; it is the model that possess the impact of volatility types on the returns of investors in the corn market.

Stock Return Volatility and Pass-through estimates: In this section, the paper makes use of different plausible models to estimate stock return volatility. This is conducted by considering both systematic and idiosyncratic volatility sources and consequently, the paper compares the performance of the estimations by bearing in mind varying corn portfolios, equal and value weighted volatility. Model selection criteria used for the selection of appropriate model of return volatility of corn are Schwarz Information Criterion (SIC. Akaike Information Criterion (HIC) and HQC. The volatility results also present some post-estimation analyses using ARCH LM test to validate the presence of heteroscedasticity in the selected volatility estimates.

[1]Check Liu and Narayan (2010) for further clarification on derivations.

Table 1. Descriptive Statistics of Volatility Series

Panel A: Summary Statistics						
Details	**Mean**	**Median**	**StdDev**	**Coef.V**	**Skewness**	**JB**
SVolew	0.0201	0.0203	0.0112	0.2783	-0.1045	1.0123
SVolvw	0.0157	0.0184	0.0083	0.3674	-0.0827	1.0104
IVolew	0.0113	0.0146	0.0078	0.3106	-0.0549	2.0112
IVolvw	0.0786	0.0073	0.0049	0.2984	-0.0378	2.0062
Panel B: Correlation Statistics						
	SVolew	SVolvw	IVolew	IVolvw		
SVolew	1					
SVolvw	0.8016	1				
IVolew	0.8439	0.5533	1			
IVolvw	0.7155	0.7921	0.7309	1		
Panel C: Autocorrelation Table						
	SVolew	SVolvw	IVolew	IVolvw		
$\rho 1$	0.524	0.457	0.723	0.689		
$\rho 3$	0.446	0.343	0.682	0.622		
$\rho 6$	0.208	0.198	0.514	0.595		
$\rho 9$	0.195	0.124	0.483	0.479		
$\rho 12$	0.183	0.153	0.43	0.374		

Table 2. Unit root test with two structural breaks

Stock Volatility Types	**Model 1**			**Model 2**		
	Test Statistic	**TB1**	**TB2**	**Test Statistic**	**TB1**	**TB2**
Systematic Volatility	-2.9831	04/09/2000	24/07/2008	-2.9852	04/09/2000	24/07/2008
Idiosyncratic Volatility	0.9482	05/09/2000	28/07/2008	0.9502	05/09/2000	28/07/2008

Note: Estimates are drawn from the Narayan and Popp (2010) unit root test procedure. Critical values at the 1% and 5% levels are 4.672 and 4.081. The sample ranges from 02/01/2000 to 28/12/2017.

Table 3. Results of volatility models with seasonal shifts for systematic case

Variable	**Asymmetric Models**	**Symmetric Models**		
Value Weighted Estimates	**EGARCH (1, 1)**	**TGARCH (1, 1)**	**GARCH (1,1)**	**GARCH-M (1, 1)**
Mean Equation				
Alpha	0.0041 (0.8322)	0.0005 (0.5722)	0.0002 (0.4276)	-0.0002 (-0.3081)
Beta	-0.0089 (-1.6149)	-0.0208 (-1.9803)	-0.0112 (-1.2102)	-0.0039 (-1.0527)
Delta	3.29*10^7 (3.2984)**	0.0008 (3.2097)**	0.0001 (2.7812)**	0.0003 (2.8133)**
Theta	0.0003 (0.4282)	0.0003 (0.4435)	0.0003 (0.4219)	0.0004 (0.2172)
Conditional Variance	-	-	-	0.0259 (1.0056)
Variance Equation				
Alpha	-0.2064 (-8.1508)*	4.29*10^5 (3.8923)*	4.98*10^5 (3.2091)*	4.88*10^5 (3.8730)*
Beta	-	0.0592 (6.9831)*	0.0278 (10.5470)*	0.0309 (12.7760)*
Lamda	-	0.8217 (9.0023)*	0.7437 (8.6727)*	0.8014 (10.0598)*
Phile	-	0.0049 (0.7638)	-	-
Rho	0.1472 (10.2086)*	-	-	-
Tau	-0.0142 (-2.6591)**	-	-	-
Sigma	0.7739 (5.4028)*	-	-	-
Diagnostic Statistics				
AIC	-4.9935	-4.9320	-4.9109	-4.9106
SIC	-4.8931	-4.8856	-4.9086	-4.9083
HQC	-4.8826	-4.8811	-4.9101	-4.9078
ARCH LM Test (7)				
F-Test	1.8069	1.5572	1.7209	1.7091
nR^2	1.8609	6.0982	5.8044	7.2206
No of Observation	884	884	884	884
Equal Weighted Estimates	EGARCH (1, 1)	TGARCH (1, 1)	GARCH (1,1)	GARCH-M (1, 1)
Mean Equation				
Alpha	0.0027 (0.7062)	0.0004 (0.2092)	0.0002 (0.4276)	-0.0002 (-0.3081)
Beta	-0.0089 (-1.7140)	-0.0318 (-1.2803)	-0.0112 (-1.2102)	-0.0039 (-1.0527)
Delta	2.42*10^6 (3.5491)**	0.0006 (2.9473)**	0.0001 (2.7812)**	0.0003 (2.8133)**
Theta	0.0002 (0.5009)	0.0008 (0.3851)	0.0003 (0.4219)	0.0004 (0.2172)
CVariance	-	-	-	0.0259 (1.0056)
Variance Equation				
Alpha	-0.1424 (-8.2398)*	3.11*10^6 (3.0243)*	3.88*10^6 (4.9501)*	4.32*10^6 (3.8609)*
Beta	-	0.0616 (5.1131)*	0.0678 (9.1573)*	0.0579 (10.3860)*
Lamda	-	0.5231 (7.2323)*	0.7238 (7.0085)*	0.8009 (9.1738)*
Phile	-	0.0052 (0.6447)	-	-
Rho	0.2097 (9.8160)*	-	-	-
Tau	-0.0112 (-3.0191)**	-	-	-
Sigma	0.6506 (3.9988)*	-	-	-
Diagnostic Statistics				
AIC	-4.9035	-4.9010	-4.9007	-4.9003
SIC	-4.8887	-4.8862	-4.8858	-4.8848
HQC	-4.8646	-4.8635	-4.8627	-4.8618
ARCH LM Test				
F-Test	1.7892	1.6589	1.5918	1.5904
nR^2	1.7465	5.1108	5.7345	6.2091
No of Observation	884	884	884	884

The paper estimated the volatility of corn returns through the symmetric and asymmetric models. The symmetric volatility models consist of the GARCH (1, 1) and GARCH in mean (GARCH-M (1, 1). while the asymmetric volatility models are Threshold GARCH (TGARCH (1, 1)) and Exponential GARCH (EGARCH (1, 1)). A significant contribution of this paper as far as modeling of corn return volatility is concerned, is that it considers structural breaks. Apart from this, the volatility modeling approach adopted has made it possible to accommodate the time varying conditional heteroscedasticity of corn price return and also evaluate the mean reverting property of the corn return volatility. The mean and variance equations for the GARCH (1, 1) model are presented as follows:

$$\sigma_t^R = \mu + \partial\sigma_{t-1}^R + \phi_1 B_{1,t} + \phi_2 B_{2,t} + \nu_t \qquad (7)$$

Equation (7) is the mean equation and the variance equation is as follow:

$$\sigma_t^2 = \beta_0 + \beta_1 \nu_{t-1}^2 + \beta_2 \sigma_{t-1}^2; \qquad \beta_0 \succ 0, \quad \beta_1 \geq 0, \quad \beta_2 \geq 0 \qquad (8)$$

Where $B_{i,t} = 1$ if $t \geq TB_i$ and zero otherwise; $TB_i(i = 1,2)$ represented the selected breaks (see Table 2). Note that $\nu_t = \sigma_i e_t$ and e_t is standard normally distributed with unit variance. The GARCH in mean shows the effect of the conditional variance in the mean equation, and therefore, the mean equation is modified by including the conditional variance the return model:

$$\sigma_t^R = \alpha_0 + \alpha_1 \sigma_t^2 + \alpha_2 \sigma_{t-1}^R + \varphi_1 B_1 + \varphi_2 B_2 + \varepsilon_t \qquad (9)$$

As said earlier, the asymmetric volatility models considered are TGARCH (1, 1) and EGARCH (1, 1). The two models have their mean equation as shown in equation (7) and the variance equations are specified as follows:

$$In(\sigma_t^2) = \mu + \phi\left|\sqrt{\nu_{t-1}^2/\sigma_{t-1}^2}\right| + \gamma\sqrt{\nu_{t-1}^2/\sigma_{t-1}^2} + \pi In(\sigma_{t-1}^2) \qquad (10)$$

The variance of the EGARCH model is specified in equation (10. while the variance of the TGARCH model is expressed as:

$$\sigma_t^2 = \delta_0 + \delta_1 \nu_{t-1}^2 + \delta_2 \sigma_{t-1}^2 + \varphi \nu_{t-1}^2 I_{t-1} \qquad (11)$$

Where $I_{t-1} = 1$ if $\nu_{t-1} \succ 0$ (positive shocks) and $I_{t-1} = 0$ otherwise; and therefore, there is evidence of asymmetric effect if $\varphi \prec (\succ) 0$ which implies that positive (negative) shocks reduce the volatility of σ_t^R by more than negative (positive) shocks of the same proportion. Table 3 and 4 show the results of the several volatility models for both systematic and idiosyncratic volatility forms. The implication of the results is that, the variance process reverts to its mean slowly for all the models and irrespective of the volatility form. This is inferred from the addition of the ARCH and GARCH effects of the variance equations that are close to one, therefore indicating that the variance process reverts slowly although the systematic volatility form reverts quickly than the idiosyncratic one. The slow mean reverting process is an indication of high level of volatility persistence in the price of corn. In this case, price of corn with intense idiosyncratic volatility appear more persistent than that with systematic volatility. The findings are consistent with the descriptive statistics presented in Table 1. Comparing the performance of the two volatility forms given the models, the GARCH (1, 1) model appears to produce a better fit over the GARCH in mean (GARCH-M (1, 1)) model for the symmetric volatility models. This is reached with the SIC value. This is not striking as such, as the inclusion of the coefficients on the standard deviation of the corn price returns in the conditional mean equation, is statistically not significant and therefore, does not provide any useful information as to the volatility models (i.e. systematic and idiosyncratic models). Similarly, the estimates of TGARCH (1, 1) provide an inferior result when compared to the EGARCH (1, 1) for the case of asymmetric. In all, the EGARCH (1, 1) model offers a better fit when compare to the GARCH (1, 1) in the symmetric case. In addition, the results of the EGARCH model suggest that there are leverage effects in both volatility models – idiosyncratic and systematic volatility forms. This is inferred from the findings, as the variable measuring the leverage effects is negative for both return volatility forms. The implication therefore, is that negative shocks have tendency of reducing volatility more than positive shocks in the corn market. It also show that investors in the corn market react more to bad news, as bad news has immense potential of increasing volatility than good news. In the descriptive statistics, it is evident that there is presence of ARCH effects in the return volatility series (i.e. systematic and idiosyncratic volatility); thus, necessitating the estimation of the post-estimation diagnostic tests to ascertain if the volatility models have accommodated the effects. These is the reason why the ARCH tests is conducted using both F-test and chi-square distributed (nR^2) test. The results show that in all the estimations the acceptance of the null hypothesis of no ARCH effects is appropriate. All the values are statistically not significant. Summarily, the findings show that with structural breaks in volatility series, the exponential GARCH (EGARCH (1, 1)) is superior to other GARCH variants considered in the paper. Hence, more appropriate to model volatility of corn returns, more specifically in period of seasonal shifts.

Estimation of the pass-through effects of volatility to stock returns: Results of the kalman filter approach present the pass-through effects of volatility to corn returns. The measurement and transition values are shown in Table 5. Panel A-1 shows that high equal weighted systematic volatility has a negative initial state value, which indicates that returns of firms that are characterized with high equal weighted systematic volatility falls as systematic volatility rises due to structural change. Conversely, firms with medium and low equal weighted systematic volatility have positive effects. For the transition periods, specifically 2015/2016, the results show that the impact rises for all classifications – high, medium and low, respectively. The value weighted systematic volatility has similar effects. The results are statistically significant for most of the estimations as shown by the Chow F-test and appeals that the structural shifts in corn has reduced the returns generated from corn with high systematic volatility. Panel A-2 shows that the effects of value weighted systematic volatility on corn's returns are positive for high systematic volatility. That is, returns oncorn with high value weighted systematic volatility increases as the volatility rises. The transition periods also exhibit similar effects. Panel B-1 shows the results of the idiosyncratic volatility effects on returns on corn when sorted with equal weighted idiosyncratic volatility. It demonstrates that firms with high equal weighted idiosyncratic volatility have their returns increase with rising idiosyncratic volatility

Table 4. Results of volatility models with seasonal shifts for idiosyncratic case

Variable	Asymmetric Models	Symmetric Models		
Value Weighted Estimates	**EGARCH (1, 1)**	**TGARCH (1, 1)**	**GARCH (1,1)**	**GARCH-M (1, 1)**
Mean Equation				
Alpha	-0.0001 (-0.7082)	-0.0002 (-0.4278)	4.02*10^6 (0.2246)	0.0007 (1.1031)
Beta	0.0375 (3.1091)*	0.0402 (3.0803)*	0.0204 (3.0214)*	0.0339 (2.8793)**
Delta	0.0007 (2.2004)**	0.0005 (2.0192)**	0.0007 (2.8503)**	0.0014 (2.0103)**
Theta	0.0003 (0.5089)	0.0004 (0.7058)	0.0006 (0.6739)	0.0004 (0.6544)
Conditional Variance	-	-	-	-0.0518 (-1.1576)
Variance Equation				
Alpha	-0.2117 (-10.1218)*	5.28*10^5 (5.2203)*	4.58*10^5 (6.6201)*	4.37*10^5 (5.9030)*
Beta	-	0.0849 (4.1991)*	0.0583 (12.6220)*	0.0679 (15.3260)*
Lamda	-	0.7907 (9.1241)*	0.8828 (9.8932)*	0.8812 (12.1438)*
Phile	-	0.0209 (3.7855)*	-	-
Rho	0.1784 (7.0056)*	-	-	-
Tau	-0.0125 (-3.6071)*	-	-	-
Sigma	0.5639 (3.4918)*	-	-	-
Diagnostic Statistics				
AIC	-4.9735	-4.9180	-4.9310	-4.9192
SIC	-4.9383	-4.8836	-4.9196	-4.9190
HQC	-4.9306	-4.8902	-4.9275	-4.9107
ARCH LM Test				
F-Test	0.0372	0.2682	0.2147	0.3421
nR^2	0.0369	0.2676	0.2134	0.3586
No of Observation	884	884	884	884
Equal Weighted Estimates	EGARCH (1, 1)	TGARCH (1, 1)	GARCH (1,1)	GARCH-M (1, 1)
Mean Equation				
Alpha	-0.0002 (-0.6983)	-0.0003 (-0.5308)	4.02*10^6 (0.2246)	0.0007 (1.1031)
Beta	0.0328 (3.0119)*	0.0396 (3.0874)*	0.0204 (3.0214)*	0.0339 (2.8793)**
Delta	0.0006 (2.3204)**	0.0004 (2.1196)**	0.0007 (2.8503)**	0.0014 (2.0103)**
Theta	0.0002 (0.6129)	0.0003 (0.8858)	0.0006 (0.6739)	0.0004 (0.6544)
Conditional Variance	-	-	-	-0.0518 (-1.1576)
Variance Equation				
Alpha	-0.2081 (-11.3518)*	4.54*10^5 (6.4313)*	4.26*10^5 (5.7207)*	4.39*10^5 (6.2203)*
Beta	-	0.0887 (5.3011)*	0.0517 (10.3420)*	0.0507 (13.1173)*
Lamda	-	0.7634 (8.4081)*	0.6709 (9.5332)*	0.8055 (12.1078)*
Phile	-	0.0221 (3.8066)*	-	-
Rho	0.2008 (8.1256)*	-	-	-
Tau	-0.0137 (-3.2911)*	-	-	-
Sigma	0.4093 (3.2968)*	-	-	-
Diagnostic Statistics				
AIC	-4.9734	-4.9250	-4.9370	-4.9197
SIC	-4.9595	-4.8906	-4.9301	-4.9105
HQC	-4.9310	-4.8916	-4.9289	-4.9087
ARCH LM Test				
F-Test	0.0375	0.2656	0.2176	0.3439
nRSquared	0.0371	0.2651	0.2172	0.3508
No of Observation	884	884	884	884

Note: *, ** indicate 1% and 5% levels of significance.

Table 5. Impact of seasonal shift on returns through volatility

Panel A-1: Returns sorted with Systematic Volatility (SVol) - Equal Weighted									
Returns	***Measurement Results***			***Transition Results***				***Chow Test***	
	theta_zero	*Prob.*	*R-Squared*	*gamma(2009)*	*gamma(2010)*	*gamma(2011)*	*gamma(2012)*	*F-Stats*	*Prob.*
High	-2.757	0.047	13.27%	-1.937**	-1.028**	-1.011	-1.004**	3.112	0.001
Medium	4.203	0.039	5.25%	0.983	1.422**	1.891**	0.762**	2.178	0.022
Low	1.895	0.053	17.42%	0.557**	1.211**	0.994**	1.024**	2.584	0.006
Panel A-2: Returns sorted with Systematic Volatility (SVol) - Value Weighted									
High	-0.801	0.983	12.97%	-0.621**	-0.49**	1.149**	1.501**	3.002	0.002
Medium	-1.416	0.973	4.60%	-1.224**	-1.005**	-0.918	-0.766**	1.944	0.043
Low	-4.23	0.892	17.22%	0.755**	-0.946**	-0.427**	-0.331**	3.024	0.002
Panel B-1: Returns sorted with Idiosyncratic Volatility (IVol) - Equal Weighted									
Returns	*Measurement Results*			*Transition Results*				*Chow Test*	
	theta_zero	*Prob.*	*R-Squared*	*gamma(2009)*	*gamma(2010)*	*gamma(2011)*	*gamma(2012)*	*F-Stats*	*Prob.*
High	3.525	0.045	10.19%	2.101**	1.877	1.652**	1.009**	2.002	0.037
Medium	8.297	0.011	5.20%	6.992**	7.104**	5.212	6.725**	2.153	0.024
Low	-3.929	0.052	6.83%	-2.117**	-1.566**	0.983**	1.009**	1.806	0.064
Panel B-2: Returns sorted with Idiosyncratic Volatility (IVol) - Value Weighted									
High	2.834	0.057	12.00%	1.641**	1.019**	1.994**	2.017**	1.908	0.048
Medium	3.064	0.186	2.08%	2.409**	1.887	1.952	2.101**	1.867	0.054
Low	4.093	0.37	4.98%	3.399**	3.245**	2.871**	3.095**	2.116	0.026

*Note: ** denotes statistical significant of variables at 5% level*

Source: Author's computation and compilation, underlying output contains several regression results.

caused by structural change. The implication is that investors in corn will have to receive increase but low returns when compared with the rate of increase in the idiosyncratic volatility. Furthermore, the initial state coefficient (theta zero) was positive in value and the chow F-test was also significant. This supports the earlier findings that as idiosyncratic volatility rise as a result of the seasonal shifts, returns earned by investors on corn with high equal weighted volatility will rise but not proportionally. Similar results were observed for stocks with medium equal weighted idiosyncratic volatility. During the transition period, it is observed that cornprices with low idiosyncratic volatility earn higher returns on the average. Panel B-2 gives positive and increase trends for all the returns irrespective of the cornvolatility classes – high, medium and low cases. The transition models show that the effect of value weighted idiosyncratic volatility on corn returnsis positive for all estimations. This therefore implies that, corn returns remain positive strong with increasing value weighted idiosyncratic volatility.

The relationship between corn returns and value weighted idiosyncratic volatility is monotonic increase and in such case, the effect of the structural shift have increasing effect on corn returns that are characterized with idiosyncratic volatility that accounts for the value of transactions. In sum, the theta zero for both medium and low value weighted idiosyncratic volatility models were not significant, but the chow F-test confirm the existence of the impact of the seasonal shift on corn returns through volatility. Concluding Remarks

Modeling volatility of corn returns provides crucial information to investors and actors, more particularly; it reveals the level of risk presence in corn prices. In essence, variability in corn prices implies significant losses (gains) in investments and therefore, decreases (increases) returns of investors in corn prices. As a profit maximizing investor, with a risk averse investment interest, the incidence of persistent high volatility will impact on the diversification of investor's portfolio either to a less risky assets or to more volatile asset class. Therefore, modeling corn returns volatility has major policy relevance for investors and investors in agricultural produces.

The NP unit root test procedure shows that there are two structural breaks in corn returns volatility. These occur in 2015/2016 and 2018. These two seasonal shifts substantially affected corn prices and consequently its volume of investment. The estimations show that there is persistence in the corn returns volatility irrespective of volatility types. However, the idiosyncratic volatility type appears more persistent than systematic volatility. The results also show the evidence of leverage effects in both volatility types, and therefore, investors in cornprices react to news. More importantly, the findings show that bad news has the possibility of increasing volatility in the returns of corn prices than good news. Furthermore, relatively, the asymmetric models seem more appropriate in modeling stock return volatility than the symmetric approach. Particularly, the exponential GARCH (EGARCH) model produces the best fit and therefore, the paper proposes that the EGARCH should be considered when dealing with corn return volatility. The paper further examined the effect of volatility types on corn returns and findings show that there are positive effects of volatility types, regardless of types and values of corn activities. In sum, the paper recommends the consideration of asymmetric effects as well as seasonal shifts when modeling corn return volatility.

REFERENCES

Aliyu, U. R. 2011. "Does inflation has an impact on stock returns and volatility? Evidence from Nigeria and Ghana", International Conference on Economics and Finance Research IPEDR, Vol. 4 (2011), IACSIT Press, Singapore.

Ang, A., Hodrick, R. J., Xing, Y. and Zhang, X. 2006. "The cross section of volatility and expected returns", Journal of Finance, Vol. 61(1), 259-299.

Bali, T. G., and Cakici, N. 2006. "Aggregate idiosyncratic risk and market returns", Journal of Investment Management, 4(4).

Bekaert, G., Hodrick, R. J. and Zhang, X. 2009. "Is there a trend in idiosyncratic volatility? Paper presented at the AFA 2009 San Francisco meetings, San Francisco.

Bekaert, G., Hodrick, R. J. and Zhang, X. 2010. "Aggregate idiosyncratic volatility", Unpublished Working Paper, Columbia University.

Brandt, M. W., Brav, A., Graham, J. and Kumar, A. 2009. "The idiosyncratic volatility puzzle: Time trend or speculative episodes? Review of Financial Studies, 23(2), 863-899.

Brockman, P., and Yan, X. S. 2008. "The time series behavior and pricing of idiosyncratic volatility: Evidence from 1926 to 1962. Working Paper series, University of Missouri – Columbia.

Brockman, P., Schutte, M. G. and Yu, W. 2010. "Is idiosyncratic volatility prices? The international evidence, Michigan Tech University.

Campbell, J. Y., Lettau, M., Malkiel, B. G. and Xu, Y. 2001. "Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk", Journal of Finance, 56 (1-43).

Campbell, J. Y., Lo, A. W. and Mackinlay, C. A. 1997. The econometrics of financial markets, Princeton University Press, Princeton – New Jersey.

Clayton, L., Dempsey, M. and Veeraraghavan, M. 2006. "Are beta, firm size, liquidity and idiosyncratic volatility related to stock returns? Australian Evidence, Working Paper Series, Monash University, Melbourne.

Dempsey, M., Drew, M. E. and Veeraraghavan, M. 2001. "Idiosyncratic risk and Australian equity returns", Working Paper series, Griffin University, Queensland.

Drew, M. E., Mallin, M., Naughton, T. and Veeraraghavan, M. 2006. "Equity premium: Does it exists? Evidence from Germany and United Kingdom" Studies in Economics and Finance, Vol., 23(2), pp. 80-93.

Emenuga, C. A. 1994. Systematic factors and returns on equities in the Nigerian Securities Market", Unpublished PhD Thesis, Department of Economics, University of Ibadan, Nigeria.

French, K., Schwert, G. W. and Stambaugh, R. 1987. "Expected stock returns and volatility", *Journal of Financial Economics,* 19, 3-30.

Fu, F. 2009. "Risk and the cross section of expected stock returns" Journal of Financial Economics, 91, 24-37.

Gao, X., Yu, J. and Yuan, Y. 2010. "Investor sentiment and idiosyncratic risk puzzle", Working paper series, University of Hong Kong, Hong Kong.

Gilbert, C. L. 2010. "How to understand high food prices", *Journal of Agricultural Economics,* 61: 398-425.

Hamao, Y., Mei, J. and Xu, Y. 2003. "Idiosyncratic risk and creative destruction in Japan", Unpublished Working Paper, NBER.

Goyal, A. and Santa-Clara, P. 2003. “Idiosyncratic risk matters!” *Journal of Finance,* 58, 975-1007.

Kalu, E. O. 2008. “Modelling stock returns volatility in Nigeria using GARCH models”, Department of Banking and Finance, University of Nigeria, Enugu Campus, Enugu State, Nigeria.

Liu, R., and Narayan, P. K. 2010. “A new structural break unit root test based on a GARCH model”.

Lundblad, C. 2007. “The risk return tradeoff in the long run: 1836-2003”, *Journal of Financial Economics,* 85, 123-150.

Malkiel, B. G., and Xu, Y. 2006. “Idiosyncratic risk and security returns” Princeton University & The University of Texas at Dallas.

Minot, N. 2014. “Food price volatility in sub-Saharan Africa: Has it really increased?” Food Poicy 45: 45-56.

Mustapha, S. A. 2015. Asset Volatility and Pricing in the Nigerian Stock Market, Unpublished PhD Thesis, Department of Economics and Statistics, University of Benin, Benin City, Nigeria.

Mustapha, S. A. 2017. “Stock (Mis) Pricing and Investment Dynamics in Africa” Evidence from African Equities”, African Development Bank Working Paper Series No. 278, African Development Bank Headquarters, Cote D’Ivoire, Abidjan.

Narayan, P. K., and Popp, S. 2010. “A new unit root test with two structural breaks in level and slope at unknown time”, Journal of Applied Statistics, 37 (9. 1425-1438.

Nartea, G. V., and Ward, B. D. 2009. “Does idiosyncratic risk matter? Evidence from the Philippine Stock Market”, *Asian Journal of Business and Accounting,* 2 (1&2. 47-67.

NSE (2012. NSE factbook, Nigerian Stock Exchange, 2012 Edition.

Wei, S. X. and Zhang, C. 2005. “Why did individual stocks become more volatile?” *Journal of Business,* 79(1. 259-292.

Wilhelmsson, A. 2006. “GARCH forecasting performance under different distribution assumptions”, *Journal of Forecasting,* 25, 561-578.

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