On the Application of Generalized Beta-G Family of Distributions to Prices of Cereals

Rasaki Olawale Olanrewaju

Pan African University Institute for Basic Sciences, Technology, and Innovation (PAUSTI), Nairobi, Juja, Kenya
Email: rasakiolawale@gmail.com; olanrewaju_rasaq@yahoo.com

How to cite this paper: Olanrewaju, R.O. (2021) On the Application of Generalized Beta-G Family of Distributions to Prices of Cereals. *Journal of Mathematical Finance*, **11**, 670-685.
https://doi.org/10.4236/jmf.2021.114036

Received: October 24, 2021
Accepted: November 21, 2021
Published: November 24, 2021

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Abstract

Generalized Beta-G family of distributions proposed has alternative distributions to unbounded distributions for modeling price returns. In contrast to Gaussian and other unbounded distributions that take values from $(-\infty, \infty)$, Generalized Beta-G family of distributions takes values from $[0, \infty)$ so as to properly contain only positive valued observations like that of price returns. In line with this, Nine (9) befitting candidates of the Generalized Beta-G family of distributions were proposed and subjected to monthly prices of cereals. Chen distributional random noise outstripped other candidates of the Generalized Beta-G family of distributions to produce minimum monthly standard deviations of 0.2686 (26.86%), 0.2572 (25.72%), 0.2404 (24.40%), 0.2267 (22.67%), 0.2257 (22.57%), 0.2544 (25.44%), 0.2343 (23.43%), 0.2391 (23.91%), 0.2273 (22.73%) and 0.2465 (24.65%) for prices of Rice, Maize, Sorghum, Millet, G-corn, Cowpea, Groundnut, Beans, Wheat and Cassava respectively. Chen and Loglogistic distributional random noises are the leading candidates among the Generalized Beta-G family of distributions in modelling price returns of the cereals, followed by Fréchet, Weibull and Birnbaum-Saunders random noises in order of significant. Lomax and Linear Failure Rate (LFR) are the ineffective random noises in modeling the price returns.

Keywords

Chen, Generalized Beta-G Family of Distributions, Loglogistic, Price, Cereals

1. Introduction

Over the past few years, generalization of statistical distribution has attracted much attention. The attention can be classified based on range of values the distribution (s) and subjected matter (s) is/are defined for. When the range of values defined for a distribution and the dataset are positively continuous, that is, values taken within $\Re^{+}$, distributions like Life Failure Rate (LFR), Lognormal etc. could be employed so as not to fall the victim of over-parameterization (problem of parsimony). However, when the range of values defined for the distribution and dataset takes range of values from $[0,1]$ or $(0,1)$, distributions like Beta distribution might be the ideal candidate of generalization. In a similar vein, when the range of values for both distribution and dataset takes values on the real number line, that is, $(-\infty,\infty)$, distributions like Gaussian, Gumbel, Student-t, and skew-normal etc. [1].

These distributional generalizations do not only provide robust families of distributions that integrate pliable Probability Density Functions (PDFs) or Probability Mass Functions (PMFs), but also provide ductile functions like, survival & lifetime analysis functions (both for hazard rate function), reshaping functions (like shape, rate, location, scale, skewness) and quantile function. Each function's candidates have their usefulness, for instance, the location parameter of the reshaping function usually influences the acceptance of a model (that is, the notion of location parameter brings about a better fit), while its absence usually makes a model quite appropriate [2].

Based on studies, generalizations of distributions via some of their mentioned ductile functions do provide bathtub, bathtub-shaped, upside-down bathtub [3]. Among the recently introduced generalized distributions with different appealingness for datasets and users are the new families of distributions. These distributions are Beta exponential-G family introduced by [4], Beta-G family introduced by [5], Generalized Beta-G family by [6], Exponentiated exponential Poisson-G family introduced by [7], Exponentiated-G family introduced by [8], Exponentiated Kumaraswamy-G introduced by [9], Gamma1-G family introduced by [10], Generalized transmuted-G introduced by [11], odd log-logistic-G introduced by [12] among others. Each member of the family of distributions has their own candidates of statistical distributions for statistical modeling or applications to different real life datasets, reliability studies, and importance. Most of these families of distributions are known for modeling lifetime issues, failure rate, time-varying series, price of a commodity, climate change data etc., though simulation studies can also be carried-out so as to estimate probability density function, cumulative distribution function, quantile function, generate random numbers and measures of inference (like Maximum likelihood estimates, Alkaike information criterion, Cramer-von Misses statistic, Anderson-Darling statistic) for each candidate of the distribution that belong to each families of distributions. Each member of the family of the distributions has their own peculiar attributes to applications to datasets. In this research, we shall be narrowing down our scope to Generalized Beta-G family of distributions because of its ability to model failure time events, time remission of bladder cancer patients, climate change agents, flood data, uniform and non-uniform time-varying series like price, stock returns among others. Among the Generalized Beta-G family of distributions is Birnbaum-Saunders, Chen, Weibull, Fréchet, F, Life Failure Rate (LFR), Log-logistic, lognormal and Lomax [13].

Among the few applications of the members of the Generalized Beta-G family of distributions to real life events was the application of the extended Birnbaum-Saunders distribution (Otherwise known as Marshall-Olkin extended Birnbaum-Saunders distribution) to reliability studies and fatigue failure times by [14]. Reference [15] also introduced a modified Burr III distribution called Beta-Burr III distribution and highlighted is importance in modeling problems related to actuarial science and survival analysis. They did not only derive the distribution's docile attributes like the moments (including its moment generating function), reliability, entropies and quantile functions, but also applied it to a survival data of acute myelogeneous Leukaemia of thirty-three (33) patients suffering from the disease.

Reference [16] propounded Beta Gumbel distribution and highlighted its ability to model accelerated life testing problems through earthquakes, flood frequency analysis, rainfall, sea currents, and wind speeds. Reference [17] extended the work of Reference [16] and introduced Beta modified Fréchet distribution called Beta Fréchet (BF) distribution as an extrapolation of Fréchet and Exponentiated Fréchet (EF) distributions. They applied the proposed BF distribution to two sets of data: the uncensored dataset that consist of hundred (100) observations of breaking stress of carbon fibres (in Gba); and used dataset by [18], the dataset that consist of strengths of 1.5 cm glass fibres measured at the National Physical Laboratory, England. They adopted the Maximum Likelihood method of estimation, and they were able to estimate the four embedded parameters with 95% confidence level that the BF distribution is an adequate model for modelling the two set of fibres. It is to be noted that Gumbel and Fréchet are two out of the three distributions of the Extreme-Value-Distributions (EVDs). The only notable application of Beta distribution to financial returns was when [19] presented a skewed distribution known as modified Beta distributions and applied it to Standard & Poor's/International Finance Corporation global daily price indices in United States dollars for South Africa with some inferences made. The statistical properties of the distributions were derived as well as the parameter estimation of the embedded parameters via Maximum Likelihood estimation technique. In light of this, none of the related members or real members of the Generalized Beta-G family of distributions has been applied to stock returns or price indices. The Generalized Beta-G family of distributions is a family of distributions that takes only positive values on the real number line against unbounded distributions that have been used in modeling price indices. The novelty of this work is the first ever application of the Beta-G family of distributions to financial returns of price of commodities, in contrast to its known application to survival analyzes and reliability studies. However, this piece of work will focus on the application of Generalized Beta-G family of distributions to wholesale prices of cereals in Kano state, Nigeria. The wholesale prices of the edible grains to be considered will be from 2007 to 2019. The members of the family of the Generalized Beta-G distributions to be considered are Birnbaum-Saunders, Burrxii, Chen, Gamma, Lognormal, Log-Logistic, Lomax, Weibull and Fréchet.

2. Mathematical Pro-Forma of Price Framework

Let p_0 denote the initial price for any commodity/stock returns assuming further that the evolution or time varying for such prices is via the horizon p = one year or p = one month. If the price of such commodity at p is denoted by p_t, a random variable, such that,

$$p = \frac{\ln(p_t)}{\ln(p_0)} = \ln(p_t) - \ln(p_0) \tag{1}$$

The p in Equation (1) is also known as growth rate.

Assuming G is a well-defined function on $\mathbb{R}^+$ with Cumulative Distribution Function (CDF). Let F be another well-defined CDF positioned on G to be the sphere of an increasing function in an enclosed Beta function in the following form:

$$F(p) = B(G(p,\Omega)) \tag{2}$$

Such that $B:[0,1] \to [0,1]$ and Ω being the parameter space of the well-defined G function. The CDF and Probability Density Function (PDF) of the Generalized Beta-G family of distributions can then be defined as:

$$f(p,\Theta) = \frac{c}{B(a,b)} g(p,\Omega)^{ac-1} \left[1 - G^c(p,\Omega)\right]^{b-1} \tag{3}$$

$$F(p,\Theta) = \frac{1}{B(a,b)} \int_0^{G^c(p,\Theta)} p^{a-1}(1-p)^{b-1} \partial p \tag{4}$$

$$F^{-1}(r) = G^{-c}\left(I_r^{-1}(a,b)\right) \tag{5}$$

for "r" in the range of $g(p,\Omega)$, $0 \le r \le 1$; $\Theta = \left(a,b,c,\Omega^{\mathrm{T}}\right)^{\mathrm{T}}$ is the universal parameter space of the Generalized Beta-G family of distributions with induced shape of $a > 0, b > 0, c > 0$. Ω is the parameter space of the $G(p,\Omega)$ distribution $\ni$ $g(p,\Omega)$ is its pdf. $B(a,b) = \int_0^1 p^{a-1}(1-p)^{b-1} \partial p$ & $I_{p(a,b)} = \int_0^p \frac{t^{a-1}\mathrm{e}^{-t}\mathrm{d}t}{B(a,b)}$ denotes the incomplete beta function ratio. According to [5] and [20], among the few candidates of the Generalized Beta-G family of distributions, that is, the number of independent and identically distributed random variables whose PDF follows $g(p,\Omega)$ are:

Weibull:

$$g(p,\Omega) = \frac{r}{s}\left(\frac{p-\mu}{s}\right)^{r-1} \exp\left[-\left(\frac{p-\mu}{s}\right)^{r}\right] \tag{6}$$

For $p > 0$, $p > \mu$, $\Omega = \{r,s,\mu\}^{\mathrm{T}} \ni \Omega \in \Re^+$ $\forall$ shape, rate, and location parameters respectively.

F:

$$g(p,\Omega)=B^{-1}\left(\frac{r}{2},\frac{s}{2}\right)\left(\frac{r}{s}\right)^{\frac{r}{2}}\left(1+r\frac{p-\mu}{s}\right)^{-\left(\frac{r+s}{2}\right)} \tag{7}$$

B is stands for the Beta function defined above, for $p>0$, $p>\mu$, $\Omega=\{r,s,\mu\}^{\mathrm{T}} \ni \Omega\in\Re^{+} \ \forall$ shape, scale and location parameters respectively.

Linear Failure Rate (LFR):

$$g(p,\Omega)=\left(r+s(p-\mu)\right)\exp\left\{-rp-\frac{(p-\mu)^{2}}{2}\right\} \tag{8}$$

For $p>0$, $p>\mu$, $\Omega=\{r,s,\mu\}^{\mathrm{T}} \ni \Omega\in\Re^{+} \ \forall$ shape, rate and location parameters respectively.

Chen:

$$g(p,\Omega)=rs(p-\mu)^{r-1}\exp\left((p-\mu)^{r}\right)\exp\left\{-s\left[\exp\left((p-\mu)^{r}\right)-1\right]\right\} \tag{9}$$

For $p>0$, $p>\mu$, $\Omega=\{r,s,\mu\}^{\mathrm{T}} \ni \Omega\in\Re^{+} \ \forall$ scale, shape and location parameters respectively.

Birnbaum-Saunders:

$$g(p,\Omega)=\frac{\sqrt{\frac{s}{p-\mu}}+\sqrt{\frac{p-\mu}{s}}}{2r(p-\mu)}\phi\left(\frac{\sqrt{\frac{p-\mu}{s}}-\sqrt{\frac{s}{p-\mu}}}{r}\right) \tag{10}$$

For $p>0$, $\phi(.)$ is the pdf of the standard Gaussian, $p>\mu$, $\Omega=\{s,\mu,r\}^{\mathrm{T}}$ $\ni$ $\Omega\in\Re^{+} \ \forall$ scale, location and shape parameters respectively.

Fréchet:

$$g(p,\Omega)=\frac{r}{s}\left(\frac{p-\mu}{s}\right)^{-r-1}\exp\left\{-\left(\frac{p-\mu}{s}\right)^{-r}\right\} \tag{11}$$

For $p>0$, $p>\mu$, $\Omega=\{r,s,\mu\}^{\mathrm{T}} \ni \Omega\in\Re^{+} \ \forall$ shape, scale and location parameters respectively.

Log-logistic:

$$g(p,\Omega)=\frac{r}{s^{r}}(p-\mu)^{r-1}\left[\left(\frac{p-\mu}{s}\right)+1\right]^{-2} \tag{12}$$

For $p>0$, $p>\mu$, $\Omega=\{r,s,\mu\}^{\mathrm{T}} \ni \Omega\in\Re^{+} \ \forall$ shape, scale and location parameters respectively.

Lomax:

$$g(p,\Omega)=\left(\sqrt{2\pi}s(p-\mu)\right)^{-1}\exp\left[-\frac{1}{2}\left(\frac{\log(p-\mu)-r}{s}\right)^{2}\right] \tag{13}$$

For $p>0$, $p>\mu$, $\Omega=\{r,s,\mu\}^{\mathrm{T}} \ni \Omega\in\Re^{+} \ \forall$ shape, rate and location parameters respectively.

Log-normal:

$$g(p,\Omega) = \left(\sqrt{2\pi}s(p-\mu)\right)^{-1} \exp\left[-\frac{1}{2}\left(\frac{\log(p-\mu)-r}{s}\right)^2\right] \quad (14)$$

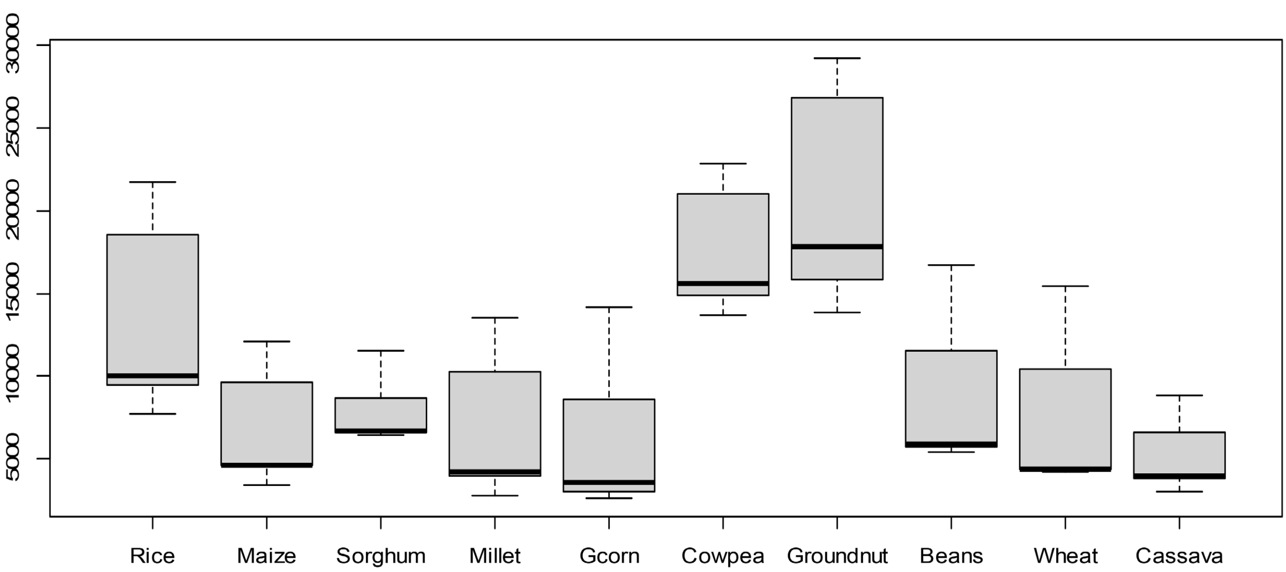
For $p > 0$, $\pi \approx 3.124$, $p > \mu$, $\Omega = \{r, s, \mu\}^{\mathrm{T}} \ni \Omega \in \Re^+ \ \forall$ shape, scale and location parameters respectively. It is to be noted that $G(p,\Omega)$ is the CDFs of the pdfs defined above, from Equation (6) to Equation (14). The parameter estimation of the universal parameter space $\Theta = \left(a, b, c, \Omega^{\mathrm{T}}\right)^{\mathrm{T}}$ can be estimated via Maximum Likelihood function of

$$L(\Theta/P) = \prod_{i=1}^{n}\left(\frac{c}{B(a,b)} g(p,\Omega)^{ac-1}\left[1-G^c(p,\Omega)\right]^{b-1}\right) \quad (15)$$

3. Numerical Analysis

The monthly-harmonized wholesale prices (in naira (#)) of cereals in Kano state, Nigeria from 2007 to 2019 would be subjected to the Generalized Beta-G family of distributions. The cereals include-rice, maize, sorghum, millet, gcorn, cowpea, groundnut, beans, wheat and cassava. The time series dataset was obtained from the Ministry of Agriculture and Natural Resources (MANR), Kano state, Nigeria. The dataset was a monthly uniform time-varying harmonized and regulated price of the edible grains by the ministry (**Figure 1**).

The median value (that is the black line between the whiskers) for all the cereal prices except for the one of groundnut for the edible grains are more closer to their bottom boxes, with their whiskers shorter on the lower part of their boxes, this suggested an extremely positively skewed distribution (rightly skewed) for all. However, the groundnut possessed the same traits, but not to the extreme like others because the whisker (black line) for the groundnut boxplot was not at the basement of the wall of the plot. In other words, groundnut's



Author's Computation (2021).

Figure 1. Boxplots of the prices of the cereals.

whisker is in between the median (50th percentile or second quartile) and first quartile (25th percentile), in contrast to others that their whiskers leveled with the first quartile. Overall, it indicated that all the prices of the edible grains are affected by frequent modestly sized deviations that would surely affect estimates if model with Gaussian distribution or unbound distributions.

From Table 1, Chen random noise gave the minimum monthly standard deviation of 0.2686 (26.86%) for the monthly price of rice with moderate magnitude of skewness and kurtosis of 0.1589 and 2.2520 respectively. Interestingly, chen distributional random noise dominated all the other Generalized Beta-G family of distributions in absolving the noise and fluctuations characterized by the prices of cereals to give minimum monthly standard deviations of 0.2572 (25.72%), 0.2404 (24.04%), 0.2267 (22.67%), 0.2257 (22.57%), 0.2544 (25.44%), 0.2343 (23.43%), 0.2391 (23.91%),0.2273 (22.73%), 0.2465 (24.65%), skewness of 0.2154, 0.3339, 0.1338, 0.1773, 0.1240, 0.3481, 0.1277, −0.0152, 0.0132 and kurtosis 2.3266, 2.6471, 2.4149, 2.6258, 2.3426, 2.9886, 2.1858, 2.3668, 2.3813 for prices of Maize, Sorghum, Millet, G-corn, Cowpea, Groundnut, Beans, Wheat and Cassava respectively.

From Table 2, Chen and Weibull are the ideal generalized distributional random noises for rice. They jointly produced the same and smallest reduced error model performance of AIC = 2973.432; CAIC = 2973.996; BIC = 2991.731; HQIC = 2980.864 with $\hat{\Theta} = (28.4031, 8.3039, 0.2916, 3.7685, 1682.6468, 7486.7712)$, where $\hat{\Omega} = (3.7685, 1682.6468, 748.7712)$. From the Anderson-Darling estimate of 9.5843, that is greater than the critical value of 0.7752, we fail to accept that the data came from normal distribution. Additionally, since the Kolomogorov-Smirnov statistic is 0.2701 with its p-value = 0.00011 < 0.05 there is no sufficient evidence that the rice price sample came from normal distribution. In addition, chen outmatched other candidates of Generalized Beta-G family of distributions in modelling the price of maize with reduced error performance of AIC = 2812.919; CAIC = 2813.482; BIC = 2831.218; HQIC = 2820.351 with $\hat{\Theta} = (0.1884, 5.2514, 0.5869, 0.1698, 0.2694, 3440.8126)$, where $\hat{\Omega} = (0.1698, 0.2694, 3440.8126)$. The Anderson-Darling of 7.1804 > 0.7752 shows that the strength of the price of the maize edible grains can be adequately described by the Generalized Beta-G family of distribution. However, since the Kolmogorov-Smirnov statistic is 0.2038 with its p-value = 0.0000 < 0.05, it is obvious that price of maize price did not emanate from Gaussian distribution. Fréchet and Loglogistic distributional random noises jointly produced ideal performance for sorghum with AIC = 2420.474; CAIC = 2421.038; BIC = 2438.773; HQIC = 2427.906, but with different parameters of $\hat{\Theta} = (1.3025, 1.0485, 3.9379, 2.3299, 13.5964, 128.5248)$ and $\hat{\Theta} = (0.2059, 0.1965, 0.3054, 9.0645, 243.2897, 6395.0221)$ respectively. Their induced parameters are $\hat{\Omega} = (2.3299, 13.5964, 128.5248)$ and $\hat{\Omega} = (9.0645, 243.2897, 6395.0221)$ with Anderson-Darlings' statistic of 12.7501 and 8.8469 > 0.7752 and joint Kolomogorov-Smirnovs' p-value = 0.0000 < 0.05. Loglogistic and LFR distributional random noises jointly outstripped other

Table 1. Coefficients of skewness, kurtosis, and standard deviation for the prices of cereals.

Rice	Weibull	Birnabum-Saunders	Chen	F	Fréchet	LFR	Log-normal	Log-logistic	Lomax
MonthlyStd Dev	0.9160	8.2093	0.2686	8.1980	2.3690	3.6767	182.3016	3.8321	1.2433
Skewness	0.6057 (0.1344)	4.5183 (4.6065)	0.1589 (0.1620)	4.5199 (4.6081)	2.4468 (2.4946)	2.4654 (3.5612)	4.4902 (4.5778)	5.3156 (5.4194)	9.3941 (9.5775)
Kurtosis	3.0919 (0.0919)	31.9927 (28.9927)	2.2520 (−0.7480)	25.6861 (22.6861)	11.9789 (8.9789)	5.6717 (3.9106)	27.4719 (24.4719)	41.5122 (38.5122)	103.6024 (100.6024)
Maize									
MonthlyStd Dev	0.9118	10.0425	0.2572	14.2570	6.7517	0.3099	182.3693	5.5786	2.3576
Skewness	0.2868 (0.2924)	2.8147 (2.8696)	0.2154 (0.2197)	6.0355 (6.1533)	7.2594 (7.4011)	0.9326 (0.9508)	6.7469 (6.8786)	6.8477 (6.8786)	4.3167 (3.7543)
Kurtosis	2.4606 (2.4606)	12.8122 (9.8122)	2.3266 (−0.673)	43.4280 (40.4280)	65.0128 (62.0128)	3.2869 (0.2869)	50.6347 (47.6347)	58.9935 (47.6347)	34.7172 (7.7256)
Sorghum									
MonthlyStd Dev	0.8827	9.0662	0.2404	7.8903	3.3496	0.2922	236.6115	2.3323	3.4185
Skewness	0.5483 (0.5590)	2.7273 (2.7806)	0.3339 (0.3404)	5.6829 (5.7939)	2.9632 (3.0211)	0.9184 (0.9364)	9.0870 (9.2644)	1.9766 (2.0152)	1.7256 (0.7853)
Kurtosis	2.7043 (−0.2957)	11.5328 (8.5328)	2.6471 (−0.3529)	38.1972 (35.1972)	12.9652 (9.9652)	2.8979 (−0.1021)	95.1809 (95.1809)	8.1811 (5.1811)	4.3256 (6.4577)
Millet									
MonthlyStd Dev	1.0001	10.9945	0.2267	10.6418	5.2178	0.3194	443.5991	3.1816	2.1778
Skewness	0.7705 (0.7855)	3.4827 (3.5507)	0.1338 (0.1364)	9.8992 (3.2715)	3.2472 (4.2516)	1.1351 (1.1573)	7.3584 (7.5020)	2.8564 (2.9121)	10.5606 (10.7668)
Kurtosis	2.9104 (−0.0896)	17.5067 (14.5067)	2.4149 (−0.5851)	112.6883 (109.6883)	7.4357 (12.5467)	4.0506 (1.0506)	63.0945 (60.0945)	12.1612 (9.1612)	123.6616 (120.6616)
G-Corn									
MonthlyStd Dev	0.8978	11.1932	0.2257	13.8708	0.5324	0.3192	140.8943	2.6797	0.8967
Skewness	0.2112 (0.2154)	4.6541 (4.7449)	0.1773 (0.1807)	5.6299 (5.7398)	7.2356 (2.3467)	0.9829 (1.0021)	9.6636 (9.8523)	3.5679 (3.6376)	7.3981 (7.5425)
Kurtosis	2.5665 (−0.4335)	33.5766 (30.5766)	2.6258 (−0.3742)	36.4662 (33.4662)	23.24352 (56.2461)	3.1701 (0.1701)	105.0269 (102.0269)	19.5677 (16.5677)	71.9099 (68.9099)
Cowpea									
MonthlyStd Dev	0.8512	8.8147	0.2544	39.7075	30.2382	0.3027	109.7695	2.6991	0.7178
Skewness	0.6392 (0.6517)	2.6730 (2.7251)	0.1240 (0.1264)	5.9637 (6.0801)	4.2917 (3.2536)	0.9304 (0.9486)	4.0649 (4.1442)	2.8982 (2.9548)	5.0566 (5.1553)

Continued

Kurtosis	3.1955 (0.1955)	10.9308 (7.9308)	2.3426 (−0.6574)	42.1433 (39.1433)	5.2142 (2.1826)	3.5416 (0.5416)	20.3783 (17.3783)	16.1041 (13.1041)	35.5875 (32.5875)
Groundnut									
MonthlyStd Dev	0.9267	10.3373	0.2343	17.2021	2.7560	0.3308	438.7740	3.2202	2.1242
Skewness	0.4185 (0.4267)	2.7455 (2.7990)	0.3481 (0.3549)	6.1534 (6.2735)	3.9229 (3.9995)	1.2217 (1.2455)	8.8071 (8.9790)	3.0847 (3.1449)	2.7455 (2.7990)
Kurtosis	2.9254 (−0.0746)	10.8047 (7.8047)	2.9886 (−0.0114)	43.7856 (40.7856)	22.8987 (19.8987)	3.7900 (0.7900)	81.3375 (78.3375)	14.0798 (11.0798)	10.8047 (7.8047)
Beans									
MonthlyStd Dev	0.8577	7.5464	0.2391	52.9837	4.5063	0.3239	103.6060	4.5063	1.8774
Skewness	0.7500 (0.7647)	2.4527 (2.5005)	0.1277 (0.1302)	9.8622 (10.0547)	4.2262 (4.3087)	1.4355 (1.4635)	5.0355 (5.1338)	4.2262 (4.3087)	7.9103 (8.0647)
Kurtosis	4.1828 (1.1828)	9.5973 (6.5973)	2.1858 (−0.8142)	108.2008 (105.2008)	24.8323 (21.8323)	6.3079 (3.3079)	33.0210 (30.0210)	24.8323 (21.8323)	67.4502 (64.4502)
Wheat									
MonthlyStd Dev	1.0392	9.5383	0.2273	19.1155	3.5880	0.3182	219.1932	3.3448	3.3448
Skewness	0.7992 (0.8148)	2.5659 (2.6160)	−0.0152 (−0.0155)	6.9081 (7.0429)	5.0248 (5.1229)	1.1461 (1.1685)	4.8007 (4.8944)	3.2408 (3.3041)	3.2408 (3.3041)
Kurtosis	3.7025 (0.7025)	11.0449 (8.0449)	2.3668 (−0.6332)	55.7194 (52.7194)	38.5132 (35.5132)	1.1565 (1.1565)	27.1498 (24.1498)	16.5721 (13.5721)	16.5721 (13.5721)
Cassava									
MonthlyStd Dev	0.9636	12.0795	0.2465	30.5059	12.0795	0.3144	128.0633	2.3483	1.1944
Skewness	0.6517 (0.6644)	3.4383 (3.5055)	0.0132 (0.0134)	8.8221 (8.9943)	0.0132 (0.0134)	0.9114 (0.9292)	7.3775 (7.5215)	3.5322 (3.6011)	6.0366 (6.1545)
Kurtosis	2.8589 (−0.1411)	16.5949 (13.5949)	2.3813 (−0.6187)	90.2360 (87.2360)	16.5949 (13.5949)	3.4208 (0.4208)	69.8926 (66.8926)	23.0768 (20.0768)	43.2602 (40.2602)

Generalized Beta-G family of distributions for price of millet with joint the same and smallest model performance of AIC = 2840.652; CAIC = 2841.216; BIC = 2858.951; HQIC = 2848.084, with the same $\hat{\Theta} = (0.1744, 0.1640, 0.6688, 7.5087, 1400.7276, 2779.6405)$, where $\hat{\Omega} = (7.5087, 1400.7276, 2779.6405)$, the same Anderson-Darling estimate of 8.7738 > 0.7752 and Kolomogorov-Smirnovs' p-value = 0.0000 < 0.05. Fréchet distributional random noise produced the ideal performance for price of gcorn with AIC = 2760.405; CAIC = 2241.564; BIC = 2778.704; HQIC = 2767.956 with $\hat{\Theta} = (0.1887, 0.2012, 1.1480, 2.8519, 712.9693, 2598.7736)$, such that the induced parameter is $\hat{\Omega} = (2.8519, 712.9693, 2598.7736)$. Its Anderson-Darling estimate

Table 2. Model adequacy for the generalized Beta-G family of distributions with the prices of cereals.

Rice	a	b	c	$\hat{r}$	$\hat{s}$	μ	AIC	CAIC	BIC	HQIC	CM	AD	Moran	KS
Birnbaum-Saunders	28.4031	8.3039	0.2916	3.7685	1682.6468	7486.7712	2977.357	2977.921	2995.656	2984.789	1.3008	7.2123	1255.957	0.2016 (0.0154)
Chen	0.4519	0.2547	0.1411	2.3866	3288.2655	7724.9125	2973.432	2973.996	2991.731	2980.864	1.9721	9.5843	1255.722	0.2701 (0.00011)
Weibull	0.4519	0.2548	0.1411	2.3866	3288.2655	7724.9125	2973.432	2973.996	2991.731	2980.864	1.9721	9.5843	1255.722	0.2701 (0.00011)
F	3.8475	9.2462	0.3715	0.2804	3.3708	155.2422	2977.281	2977.845	2995.58	2984.714	1.1119	6.4234	1257.936	0.1847 (0.0323)
Fréchet	25.4596	8.3861	1.5219	1.0919	65.78854	148.1611	2983.536	2984.1	3001.835	2990.969	1.1045	6.4836	1258.369	0.1884 (0.0208)
Lfr	1.0000	1.0000	1.0000	0.02880	0.0008	155.2611	2979.772	2980.336	2998.071	2987.204	2.58159	12.582	1266.628	0.2897 (0.0354)
Lomax	0.16934	0.1589	0.6927	7.6922	2270.2848	7712.4164	2980.983	2981.547	2999.282	2988.415	0.7550	5.1823	1258.116	0.1837 (0.0361)
Log-logistic	0.16934	0.1589	0.6927	7.6922	2270.2848	7712.4164	2980.983	2981.547	2999.282	2988.415	0.7550	5.1823	1258.116	0.1837 (0.0361)
Log-normal	3.6907	0.2766	2.5505	11.1753	1.2720	7728.1264	2983.876	2984.44	3002.175	2991.308	1.2182	6.7156	1262.45	0.1954 (0.0091)
Maize														
Birnbaum-Saunders	10.2835	3.4280	0.3822	2.6767	1631.1578	3446.0896	3003.467	3004.031	3021.766	3010.899	0.9984	7.3426	1296.823	0.1666 (0.0000)
Chen	0.1884	5.2514	0.5869	0.1698	0.2694	3440.8126	2812.919	2813.482	2831.218	2820.351	1.3165	7.1804	1263.686	0.2038 (0.0000)
Weibull	7.1625	7.0395	0.6610	0.3450	1685.3776	3410.2954	2818.353	2818.917	2836.652	2825.786	1.2151	6.8389	1265.078	0.1925 (0.0000)
F	2.8456	3.2580	0.8788	0.1939	8.0932	68.7615	2821.062	2821.625	2839.361	2828.494	1.0619	6.1840	1266.076	0.1785 (0.0649)
Fréchet	7.1625	7.0395	0.6610	0.3450	1685.3776	3410.2954	2818.353	2818.917	2836.652	2825.786	1.2151	6.8389	1265.078	0.1785 (0.0649)
Lfr	1.0000	1.0000	1.0000	0.0466	0.0006	69.2949	2825.977	2826.541	2844.276	2833.409	2.6844	13.0488	1277.091	0.2927 (0.0204)
Lomax	7.6905	4.1700	3.0495	0.1931	0.9413	68.6347	2829.054	2829.618	2847.353	2836.487	0.8671	5.1456	1271.813	0.1556 (0.0010)
Log-logistic	0.1425	0.1850	0.7216	8.5834	1150.6075	3422.9723	2818.308	2818.872	2836.607	2825.741	0.7927	5.0241	1265.008	0.1740 (0.0002)
Log-normal	0.3340	0.1646	2.4511	8.4786	0.5542	3451.1844	2825.492	2826.201	2832.301	2829.301	1.2024	7.0819	1289.581	0.1980 (0.0241)
Sorghum														
Birnbaum-Saunders	0.1375	10.0881	12.5006	1.9884	584.7098	6395.7448	3750.506	3751.07	3768.805	3757.938	2.9780	12.4396	1224.485	0.2788 (0.0000)
Chen	0.3012	1.7186	0.8278	0.1668	0.2116	6399.9975	2471.104	2471.667	2489.403	2478.536	2.4618	12.4796	1139.315	0.2382 (0.0000)
Weibull	0.2214	3.3432	4.1210	0.5417	431.6891	6396.1926	2477.929	2478.493	2496.228	2485.362	2.4920	12.7501	1137.413	0.2474 (0.0000)
F	1.4291	4.6612	1.2177	1.2490	4.3066	128.1713	2468.075	2468.638	2486.374	2475.507	2.0282	11.4335	1131.301	0.2165 (0.0000)

Continued

Fréchet	1.3025	1.0485	3.9379	2.3299	13.59638	128.5248	2477.929	2478.493	2496.228	2485.362	2.6132	12.7501	1224.235	0.2804 (0.0000)
Lfr	0.2059	0.1965	0.3054	9.0645	243.2897	6395.0221	2420.474	2421.038	2438.773	2427.906	1.4568	8.8469	1108.307	0.2451 (0.0000)
Lomax	1.1264	9.6833	1.5957	0.3940	1.9996	127.6777	2466.522	2467.086	2484.821	2473.954	1.9744	11.0850	1130.373	0.2131 (0.0000)
log-normal	2.2747	7.9553	5.5613	9.5948	5.0397	6386.3258	2477.773	2478.337	2496.072	2485.205	2.2954	12.2903	1136.241	0.2298 (0.0000)
log-logistic	0.2059	0.1965	0.3054	9.0645	243.2897	6395.0221	2420.474	2421.038	2438.773	2427.906	1.4568	8.8469	1108.307	0.2451 (0.0000)
Millet														
Birnbaum-Saunders	5.7542	2.6491	0.4923	2.6944	1497.5834	2796.3601	3132.641	3133.205	3150.94	3140.073	1.7230	14.7292	1362.178	0.2349 (0.0000)
Chen	0.8480	1.3493	1.0133	0.6874	0.7233	56.23826	2836.029	2836.593	2854.328	2843.462	2.0508	11.2346	1295.107	0.2644 (0.0000)
Weibull	0.9565	0.8826	0.6269	0.9570	2046.0706	2791.5023	2844.214	2844.778	2862.514	2851.647	1.9430	9.9221	1295.342	0.2682 (0.0000)
F	1.1175	3.0549	0.5924	0.2395	4.0896	56.2395	2976.966	2977.53	2995.265	2984.399	4.2889	22.8362	1368.69	0.3209 (0.0000)
Fréchet	6.4242	10.7857	1.9035	0.1803	780.8600	2791.4761	2879.922	2880.486	2898.221	2887.354	1.9370	9.8792	1314.639	0.2708 (0.0000)
Lfr	0.1744	0.1640	0.6688	7.5087	1400.7276	2779.6405	2840.652	2841.216	2858.951	2848.084	1.5104	8.7738	1292.85	0.2228 (0.0000)
Lomax	3.4899	2.3803	1.8024	0.1075	0.6952	55.8822	2873.85	2874.414	2892.15	2881.283	1.6881	9.1691	1310.544	0.2397 (0.0000)
log-normal	7.3111	0.4703	3.4760	12.1882	1.9048	2791.4286	2846.590	2847.154	2864.889	2854.023	1.7967	8.9942	1296.875	0.2595 (0.0000)
log-logistic	0.1744	0.1640	0.6688	7.5087	1400.7276	2779.6405	2840.652	2841.216	2858.951	2848.084	1.5104	8.7738	1292.85	0.2228 (0.0000)
G-corn														
Birnbaum-Saunders	0.2746	8.5421	7.9373	2.6095	1432.9010	2596.6366	3241.001	3241.564	3259.3567	3248.433	1.8036	15.4291	1277.150	0.2429 (0.0000)
Chen	0.2562	2.3567	0.4053	0.1681	0.2970	2599.7574	2782.891	2783.454	2801.190	2790.323	2.6683	14.4083	1283.767	0.2619 (0.0000)
Weibull	0.1887	0.2012	1.1480	2.8519	712.9693	2598.7736	2782.891	2783.454	2778.704	324.4482	2.6683	11.3829	1278..342	0.2492 (0.0000)
F	2.0793	2.07932	0.9569	1.3246	3.2521	52.35647	2345.467	2760.969	2801.190	3248.433	1.5210	16.5328	1288.781	0.2331 (0.0000)
Fréchet	0.1887	0.2012	1.1480	2.8519	712.9693	2598.7736	2760.405	2241.564	2778.704	2767.956	1.2616	34.5382	1267.231	0.2316 (0.0000)
Lfr	1.0000	1.0000	1.0000	0.0472	0.0012	0.00115	2825.152	2825.716	2843.451	2832.584	6.2712	34.7847	1309.552	0.4052 (0.0000)
Lomax	0.8635	9.0875	2.5479	0.3336	4.9938	52.57188	2782.891	2760.969	2778.704	324.4482	1.5269	17.4028	1280.109	0.2461 (0.0000)
log-normal	0.6315	0.3963	0.2183	6.5293	0.5520	2592.1397	2760.405	2760.969	2778.704	2767.837	1.4938	9.5550	1270.498	0.1959 (0.0000)
log-logistic	0.2623	4.2858	5.9136	0.8113	977.9292	2590.7366	2760.524	2761.088	2778.823	2767.956	1.5808	10.1875	1270.302	0.2158 (0.0000)

Continued

Cowpea														
Birnbaum-Saunders	1.6699	2.5776	1.4569	2.4955	2042.6386	13,680.9456	2912.799	2913.363	2931.098	2920.232	0.7945	5.1582	1296.013	0.1796 (0.0000)
Chen	0.4730	2.9876	2.5731	0.6871	0.4817	74.76824	2865.021	2865.585	2883.321	2872.454	0.8528	5.2554	1269.581	0.1823 (0.0000)
Weibull	6.5557	3.3789	1.3533	1.0581	53.8532	74.76824	2870.51	2871.073	2888.809	2877.942	0.8111	4.9942	1272.744	0.1726 (0.0000)
F	2.9310	3.60712	0.5712	0.2789	3.3069	74.76824	2878.586	2879.149	2896.885	2886.018	0.6827	4.7099	1275.361	0.1857 (0.0000)
Fréchet	7.7675	8.7915	1.4564	0.8478	24.4311	74.76824	2899.233	2899.797	2917.532	2906.665	0.6658	4.5100	1287.975	0.1590 (0.0000)
Lfr	1.0000	1.0000	1.0000	0.0369	0.0008	74.76824	2871.008	2871.572	2889.307	2878.44	1.5258	8.2377	1279.482	0.2070 (0.0000)
Lomax	3.6315	3.5596	2.1968	0.1219	0.6443	74.76824	2903.975	2904.539	2922.275	2911.408	0.5314	4.0018	1291.379	0.1424 (0.0000)
log-normal	1.7726	0.4814	1.1212	9.4512	2.15089	74.76824	2834.013	2402.492	2342.492	-Inf	0.7146	Inf	1298.997	0.1825 (0.0000)
log-logistic	3.8493	2.1208	2.0414	3.4906	38.26763	74.76824	2882.703	2883.267	2901.002	2890.136	0.5368	3.9252	1278.727	0.1698 (0.0000)
Groundnut														
Birnbaum-Saunders	1.8195	6.4692	5.0428	1.5900	104.8936	75.60255	Inf	Inf	Inf	Inf	2.9334	Inf	2067.818	0.3035 (0.0000)
Chen	2.2719	2.2839	1.4619	0.7774	0.3454	75.60255	2627.902	2628.465	2646.201	2635.334	1.7567	19.0272	1227.555	0.219 (0.0000)
Weibull	0.4965	1.2419	1.8254	3.0703	105.2931	75.60255	2757.028	2757.592	2775.327	2764.461	1.8129	10.9124	1288.117	0.2668 (0.0000)
F	6.3596	8.5349	1.0037	3.2629	0.6260	75.60255	3143.078	3143.634	3161.369	3150.502	5.5251	27.7554	1475.312	0.4132 (0.0000)
Fréchet	3.0031	1.0162	0.9940	1.8968	63.9483	75.60255	2757.028	2757.592	2775.327	2764.461	2.2432	10.9124	2069.387	0.2474 (0.0000)
Lfr	0.4965	1.4239	1.8254	3.0703	4.0050	75.60255	3138.075	3143.634	2646.201	2764.461	1.8129	10.9124	1288.117	0.4132 (0.0000)
Lomax	6.1093	8.4999	1.1940	4.9159	1.1469	75.60255	3146.735	3147.299	3165.034	3154.167	5.0310	26.0131	1476.675	0.3946 (0.0000)
log-normal	0.9058	1.1561	4.4326	9.4294	4.0050	75.60255	2784.069	2784.633	2802.368	2802.368	6.0558	32.7570	1305.329	0.4282 (0.0000)
log-logistic	1.5776	2.4357	2.3989	1.3672	80.3525	75.60255	2616.608	2617.171	2634.907	2624.04	6.1919	35.3184	1225.271	0.4365 (0.0000)
Beans														
Birnbaum-Saunders	0.5102	1.6791	2.8410	2.2832	1366.8216	5373.9223	2777.3	2777.864	2795.6	2784.733	1.4463	8.8857	1293.756	0.2098 (0.0000)
Chen	1.7845	3.5330	0.2204	0.1260	0.4595	5399.7257	2814.58	2815.143	2832.879	2822.012	1.8168	10.7877	1313.402	0.2345 (0.0000)
Weibull	0.1263	53.1677	8.3613	0.4213	830.3517	5357.6149	2784.121	2784.685	2802.42	2791.553	1.7070	10.3075	1296.335	0.2277 (0.0000)
F	1.2845	9.7981	0.1162	0.2055	11.2395	5402.2962	2824.472	2799.604	2816.503	2893.503	1.3998	10.593	1330.063	0.1999 (0.0000)

Continued

Fréchet	0.3244	0.6427	0.7842	2.2802	340.3627	5392.1540	2784.121	2784.685	2802.425	2791.553	1.1308	10.3075	1320.876	0.1663 (0. 0004)
Lfr	1.0000	1.0000	1.0000	0.0366	0.0005	108.4618	2875.091	2875.655	2893.393	2882.523	6.6949	46.2185	1349.467	0.4103 (0.0000)
Lomax	7.2035	6.1655	1.8608	0.3436	1.3347	108.4618	2798.773	2799.337	2817.072	2806.206	1.4980	9.3287	1303.106	0.2056 (0.0000)
log-normal	0.2677	2.7093	1.4647	4.9299	1.4083	5391.1440	2798.468	2799.032	2816.767	2805.9	1.3635	8.6541	1304.287	0.1940 (0.0000)
log-logistic	0.2278	0.2715	0.3431	6.4939	500.2135	5396.8329	2795.507	2796.071	2813.806	2802.939	1.2891	8.2339	1302.81	0.1755 (0.0000)
Wheat														
Birnbaum-Saunders	0.1776	9.0151	10.7502	3.2396	908.3830	4199.5986	3829.402	2656.045	2768.456	2498.980	5.8554	20.4562	1235.566	0.4282 (0.0000)
Chen	0.2436	2.3629	0.7507	0.1467	0.3919	4198.7916	2680.837	2681.401	2699.136	2688.269	5.1005	27.7778	1272.618	0.3787 (0.0000)
Weibull	0.1919	164.0986	8.3303	0.2827	453.9482	4181.7756	4181.7755	2609.341	2627.076	2616.209	5.7028	30.2059	1236.675	0.4192 (0.0000)
F	0.4265	37.8110	0.3025	0.4403	10.0346	4182.3229	2597.031	2597.595	2615.33	2604.463	4.7238	25.1845	1230.813	0.3739 (0.0000)
Fréchet	0.2071	7.0221	7.6517	0.4476	162.7049	4191.3308	2609.822	2610.386	2628.121	2617.255	4.3612	23.3241	1238.019	0.3433 (0.0000)
Lfr	1.0000	1.0000	1.0000	0.0614	0.0012	84.35913	2977.309	2977.873	2995.608	2984.742	15.92623	180.2937	1428.701	0.6637 (0.0000)
Lomax	0.7940	4.9003	1.9179	0.1819	1.6662	83.7864	2590.767	2591.331	2609.066	2598.2	5.1994	27.68513	1227.534	0.4005 (0.0000)
log-normal	4.1654	6.4438	6.4434	5.4767	4.6299	4195.8406	2644.185	2644.749	2662.484	2651.618	5.0688	26.9247	1254.07	0.3859 (0.0000)
log-logistic	1.0081	1.4591	0.5771	8.7772	14.7966	83.7864	2466.063	2466.627	2484.362	2473.495	4.5200	24.2533	1166.054	0.3799 (0.0000)
Cassava														
Birnbaum-Saunders	5.2914	6.5151	1.1389	2.9018	1320.0605	3039.6683	2786.764	2787.327	2805.063	2794.196	0.9858	5.7826	1221.623	0.1818 (0.0000)
Chen	1.3657	1.5499	0.8212	0.74937	0.5073	61.25659	2698.577	2699.143	2716.876	2706.009	1.4063	7.4522	1195.235	0.2397 (0.0000)
Weibull	1.8389	1.2673	0.4109	0.9997	1301.9308	3044.1806	2697.026	2697.596	2715.325	2704.458	1.1812	6.3309	1192.228	0.2120 (0.0000)
F	3.4248	4.5067	0.5772	0.1906	9.9779	61.25659	2347.970	2649.446	2344.769	2589.095	1.1874	6.9834	1222.935	0.2028 (0.0000)
Fréchet	4.7356	9.2479	1.9440	0.2752	651.7366	3039.8191	2727.405	2727.968	2745.704	2734.837	1.0401	6.2564	1208.738	0.1888 (0.0000)
Lfr	1.0000	1.0000	1.0000	0.0554	0.0009	61.2608	2700.211	2700.775	2718.51	2707.643	1.5365	7.9779	1200.618	0.2554 (0.0000)
Lomax	2.5977	5.8179	2.2661	0.2146	1.0559	61.2608	2776.833	2777.397	2795.133	2784.266	0.9690	6.9834	1227.707	0.1654 (0.0004)
log-normal	8.2770	0.2957	9.0686	11.1530	1.2148	3039.1160	2696.57	2697.134	2714.87	2704.003	1.1837	6.2859	1191.848	0.2173 (0.0000)
log-logistic	6.4027	3.6995	0.5092	0.8388	943.5924	3030.2381	2705.261	2705.825	2723.56	2712.693	1.03973	5.8317	1196.223	0.1827 (0.0000)

Keywords: inf = infinity

is 15.4291 > 0.7752 and Kolomogorov-Smirnovs' p-value = 0.0000 < 0.05. Log-normal possessed reduced-error model performance for cowpea with AIC = 2834.013; CAIC = 2402.492; BIC = 2342.492, where $\hat{\Theta} = (1.7726, 0.4814, 1.1212, 9.4512, 2.15089, 74.7648)$ and induced parameter of $\Omega = (9.4512, 2.15089, 74.7648)$ such that it's Kolomogorov-Smirnovs' p-value = 0.0000 < 0.05. Log-logistic random noise produced the ideal performance for price of groundnut with $\hat{\Theta} = (1.5776, 2.4357, 2.3989, 1.3672, 80.3525, 75.6026)$, induced parameters $\hat{\Omega} = (1.3672, 80.3525, 75.6026)$. Its Anderson-Darling estimate is 35.3184 > 0.7752 and Kolomogorov-Smirnovs' p-value = 0.0000 < 0.05.

Birnbaum-Saunders possessed the ideal reduced-error model performance for price of beans with AIC = 2777.3; CAIC = 2777.864; BIC = 2795.6; HQIC = 2784.733, where $\hat{\Theta} = (0.5102, 1.6791, 2.8410, 2.2832, 1366.8216, 5373.9233)$, such that $\hat{\Omega} = (2.2832, 1366.8216, 5373.9223)$. Its Anderson-Darling estimate is 8.8857 > 0.7752 and Kolomogorov-Smirnovs' p-value = 0.0000 < 0.05. Loglogistic is the paragon random noise for price of wheat with AIC = 2466.063; CAIC = 2466.627; BIC = 2484.362; HQIC = 2473.495, where, $\hat{\Theta} = (1.0081, 1.4591, 0.5771, 8.7772, 14.7966, 83.7864)$, such that $\hat{\Omega} = (8.7772, 14.7966, 83.7864)$. Its Anderson-Darling estimate is 24.2533 > 0.7752 and Kolomogorov-Smirnovs' p-value = 0.0000 < 0.05. Lastly, F surmounted other Generalized Beta-G distributional random noises for price of cassava with AIC = 2347.970; CAIC = 2649.446; BIC = 2344.769; HQIC = 2589.095 $\hat{\Theta} = (3.4248, 4.5067, 0.5772, 0.1906, 9.9779, 61.2566)$ such that, $\hat{\Omega} = (0.1906, 9.9779, 61.2566)$. Its Anderson-Darling estimate is 6.9834 > 0.7752 and Kolomogorov-Smirnovs' p-value = 0.0000 < 0.05.

4. Conclusion

In conclusion, Lomax and Linear Failure Rate (LFR) out of the Generalized Beta-G family of distributions are ineffective in modelling the prices of all the cereals studied. This might be due to the fact that LFR is peculiar to survival, censored and uncensored analysis. Aditionally, Lomax distribution (otherwise knwon as Pareto Type II distrbution) might be ineffectual in living-up to expectation due to its peculiarity in statistical modelling of tailedness observations, reliability studies and life testing problems in survival studies. Chen and loglogistic distributional random noises are the leading candidates among the Generalized Beta-G family of distributions in modelling of price returns, followed by Fréchet random noise. Weibull, Birnbaum-Saunders, and F distributional random noises gave un-recommendable higher error performances. Overall, all the distributional random noises for the Generalized Beta-G family of distributions gave Kolmogorov-Smirnov's p-values that are far lesser than 0.05 and Anderson-Darling estimates that are greater than the critical value of 0.7752 to affirm the model adequacy of the Generalized Beta-G family of distributions, in contrast to unbounded distributions. Among the limitations of Beta-G family of distributions is that it is for positive continuous values with single mode, and its 1 to many mapping carrier is based on either $[0,1]$ or $(0,1)$.

Acknowledgements

I personally extended gratitude to the Ministry of Agriculture and Natural Resources (MANR), Kano state, Nigeria for the provision of the prices of cereals dataset used in this project.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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