DEVELOPMENT OF ROBUST DISTRIBUTED LAG MODELS WITH EXPONENTIATED GENERALISED NORMAL ERROR TERM

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A Thesis in the Department of Statistics

Submitted to the Faculty of Science

In partial fulfilment of the requirements for the Degree of

DOCTOR OF PHILOSOPHY

of the

UNIVERSITY OF IBADAN

JUNE, 2019.

ABSTRACT

Distributed Lag Model (DLM) is a major workhorse in dynamic single-equation regression, which requires stringent assumptions for its validity. One of the critical assumptions of DLM is the normality of the Error Term (ET) which is often violated in practice and often leads to spurious inference and poor forecast performance. Violations of other assumptions had been considered in previous studies but not the Exponentiated Generalised Normal ET (EGNET) of the DLM. Therefore, this study was designed to develop a Robust DLM (RDLM) that could enhance inference when the assumption of normality of ET is violated.

Exponentiated Generalised Normal Distribution (EGND) was examined by convoluting the exponentiated link function; ( ) = [( )] ( ), where > 0 is the shape parameter, ( ) and ( ) are the probability density and distribution functions respectively with the generalised

normal distribution : are the standard $\frac{y\ \ \mu}{}\Big)\Big]$ $\frac{1}{\sqrt{\ }}\, e^{-\frac{\ }{2}\left(\frac{\ }{\sigma}\right)}$ ( ) =where σ and deviation and mean of the distribution, respectively. The DLM was then used in EGND to obtain the density function of the RDLM. The maximum likelihood method was used to estimate the parameters and the statistical properties of RDLM. The proposed model was validated with life and simulated data. Monthly data on Nigeria's gross domestic product and external reserve from 1981 to 2015 extracted from the Central Bank of Nigeria statistical bulletin were used, while data of sample sizes 20, 50, 200, 500, 1000, 5000 and 10,000 were simulated and replicated 10,000 times. For each of the simulated data, outliers were injected randomly to obtain non-normally distributed data. The performance of the proposed model was compared with DLM model with normal ET using Akaike Information Criteria (AIC), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The lower the value of the performance criteria the better the model.

The developed probability density function of RDLM was:

( ) = —— $\frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{1}{2}\frac{\left(y-\beta_o-\sum_{i=1}^{\rho}\beta_i X_{t-i}+\sum_{j=1}^{q}\alpha_j Y_{t-j}\right)}{\sigma^2}}$, where is the observed data of the response variable at time t , is the intercept, $\beta_{i,}$ ($= 1, \ldots ,$) and , $= 1, 2, \ldots ,$ are the response rates at the lags of both explanatory and response variables , respectively. The derived properties of the proposed model confirmed that EGND was a valid distribution. The simulated data of sizes 20, 50, 200, 500, 1000, 5000 and 10,000 showed AIC of 67.18, 151.58, 568.22, 1419.89, 2876. 86, 14156.15, 28220.94, respectively for DLM with normal ET. For DLM with EGNET, the AIC values were -40.01, -116.66, -282.19, -655.10, -1533.01, -3007.01, 5606.92, -26960.82, and -5283.44, respectively. For life data, DLM with EGNET performed better than DLM with normal ET as indicated by AIC values of 1590.08 and1695.19, respectively. Forecast performance indicated that RDLM was better than DLM for forecasting with lower RMSE and MAE values of 1730.50, 18348.71 and 4325.37, 30839.37, respectively.

The distributed lag model with exponentiated generalised normal error term showed improved forecasting and inference even when the residual term were not normally distributed. It is therefore recommended for normally distributed and skewed data sets.

Keywords: Distributed lag, Exponentiated generalised normal distribution, Akaike information criteria, Forecast performance.

Word count: 487

CERTIFICATION

I certify that this work was carried out by Olusesan Oluyomi **Olufolabo** in the Department of Statistics, University of Ibadan, Nigeria under my supervision.

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DEDICATION

I dedicate this research work to Almighty God, the Omnipotent, Omniscience and Omnipresent who Himself represents wisdom, knowledge and understanding in all things.

ACKNOWLEDGEMENTS

I give Glory and honour to the Almighty God for the grace, giving to me to carry out this work, with Him all things are impossible.

I will like to acknowledge the good gestures, assistances, and encouragements given by men and women of good will who have provided me with crucial help and support, academically, financially, morally and spiritually while carrying out the research for this thesis.

Firstly, I must acknowledge my supervisor Prof. O. I. Shittu. Words are not enough to express how invaluable you are to me in the course of running this programme, you always made yourself available both in and out of office even at odd hours for consultation, advice and you spent countless months in discussion of this research and provided me with ideas while keeping me on the right track despite your tight schedule. The wonderful atmosphere and constructive criticism you provided cemented my hope and confidence. God will continue to uplift you and increase your knowledge in all your endeavours.

My appreciation goes to the acting Head of the Department, Dr Angela Chukwu and all the staff of the department. I will also like to acknowledge, Dr F. O Ayoola, Dr. S. O. Osowole, Dr.O.S. Yaya, Dr C. G. Udomboso and Dr. S. O. Oyamakin for providing much help, not only through this work, but also in and out of academic work most especially during my time of need.

My appreciation also goes to Dr I. O. Badmus, Dr Adepoju Kazeem, Mr. O. Akinpeloye and Mr. O. Akintande for sharing ideas and technical assistance during the course of this project.
I highly recognise the help and encouragement I got from the following; Mr. K. O. Balogun, Mr. A. D. Babajide, Mr. and Mrs. F.O Atunbi, Dr and Dr Mrs. O.Ayannuga, Mrs. A. H. Akanbi, Mr. Kunle Ayodeji and Mr. Kehinde Nuga.

To all other people that have contributed to the success of this work directly or indirectly that I could not mention here, I say a very big thank you. God almighty will remember you for good.
Also to all my family members I say thank you for all your support and prayers.

Finally, I am very thankful to my wife and children for their love, patience, endurance, understanding, motivation, and support throughout this passage.

Olufolabo, 'Sesan Oluyomi (2019)

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ABBREVIATIONS AND DEFINITIONS

1. AIC: Akaike Information Criterion
2. BIC: Bayesian Information Criterion
3. CAIC: Consistent Akaike Information Criterion
4. DLM: Distributed Lag Model
5. EGND: Exponentiated Generalised Normal Distribution
6. ET: Error Term
7. MAE: Mean Absolute Error
8. GDP: Gross Domestic Product
9. RDLM: Robust Distributed Lag Model
10. RMSE: Root Mean Square Error
11. ARMA: Autoregressive-Moving-Average
12. ASBIAS: Absolute bias
13. P- VLAUE: Power Value
14. SD: Standard Deviation
15. Min: Minimum
16. Max: Maximum
17. 1st Qu: 1st Quantile
18. 3rd Qu: 3rd Quantile
19. CBN:Central Bank of Nigeria

20. $Y_{t:}$ represent value of Y at time t

21. X_t: represent Value of X at time t

22. y_{t-1} Values of Y at lagged values at time t

23. x_{t-1}: Values of X at lagged values at time t

24. F(y): Cumulative Function

25. f(y): Density Function

26. v: Degree of freedom

27. β: Beta

28. : Alpha

29. θ: Shape parameters

30. : Delta

31. $\sum$: Summation

32. log: Logarithms

33. l_t: Log Likelihood function at time t

34. : Sigma

35. . : Epsilon

36. π: Pie

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The practice of statistical analysis often consists of fitting a model to data, testing for violations of the estimator assumptions, and searching for appropriate solutions when the assumptions are violated (Keele and Kelly, 2006). Testing of assumptions is and should always be an important task for Statisticians or any researcher in whatever discipline making use of regression analysis, or any statistical technique for the purpose of decision making. It has been established that serious assumption violations will in most cases result in biased estimates of relationships, over or underconfident estimates of the precision of regression coefficients (i.e., biased standard errors), forecasted values and surely untrustworthy confidence intervals and significance tests (Cohen et.al., 2003, Chatterjee and Hadi, 2012). One major motivation for every statistician is to develop statistical methods or procedures that are not unduly affected by outliers or extreme values. As it has already been established that outlier in time series do cause biases in parameter estimation as well as inappropriate predictions or forecasting, resulting in misleading conclusion (Tsay, et.al. 2000).

The estimation and hypothesis testing of coefficients in a simple linear regression model is one of the oldest and most important problems that has received tremendous attention in the literature in time series and econometrics and in fact in any research field, so also the most abused by nonstatisticians (Ayinde et.al. 2012). Most of the work reported is, however, based on the assumption of normality according to Lawrence and Arthur (1990). However in recent years, it has been recognised that the underlying distribution is, in most situations, basically not normal, especially in economics and financial time series data. The solution, therefore, is to develop efficient estimators of coefficients in both simple and multiple regression models when the underlying distribution is non-normal. Naturally, one would prefer closed form estimators which are fully efficient (or nearly so). Preferably or generally these estimators should also be robust to plausible deviations from an assumed model.

Statistics with good performance for data drawn from a wide range of probability distributions, especially for distributions that does not follow a normal distribution are in general referred to as robust statistics. Robust statistical methods have been developed for many common problems, such as estimating location, scale and regression parameters. Also, another motivation for providing robust statistics model is to provide methods with good performance when there are small departures or deviations from parametric distributions. For example, robust methods work well for mixtures of two normal distributions with different standard-deviations; under this model, non-robust methods like a t-test works badly. Hence robust statistics seeks to provide methods that emulate popular statistical methods, but which are not unduly affected by outliers or other small departures from model assumptions.

In statistics, classical estimation methods like regression analysis rely heavily on basic assumptions which are often violated in practice and in particular, it is often assumed that the data errors are normally distributed, at least approximately, or that the central limit theorem can be relied upon to produce normally distributed estimates. Most unfortunately however, when there are outliers in the data, especially time series data, classical estimators often have very poor performance, when judged using the breakdown point and the influence function. Basically, forecasting remains one of the most fundamental essence for classical regression analysis. However, the classical linear regression model is formulated under some basic assumptions which are not always satisfied especially in business, economic and social sciences leading to the development of many unreliable estimators and forecasts. This was emphasised by (Ayinde et al., 2012) in their work when they examined the performances of the ordinary least square estimator, maximum likelihood estimator and the estimators based on principal component analysis (PC) in prediction of linear regression model under the violations of assumption of non – stochastic regressors, independent regressors and error terms.

1.1 Statement of the Problem

As a result of the dynamism of distributed lag models, there is in most cases a violation of normality of the residual or error term or innovation. The practice of statistical analysis often consists of fitting a model to data, testing for violations of the estimator assumptions, and searching for appropriate solutions when the assumptions are violated. Generally, applied time-series analysis depends on the diagnosis and classification of time series and the selection of appropriate models.

It is a known fact that time series data could be very complex and intractable events that require flexible, versatile and robust model to capture its essence and accommodate a wide range of conditions and possibilities that commonly prevail in skewed time series data. Previous works have not been able to adequately meet requirements particularly about the shape of the error term from the distribution perspective (Maos and Hox 2013). For instance, nonparametric model does not rely on any particular distribution and the reason being that it is a distribution free method. In non-parametric methods, disadvantage of biasedness and precision of the estimators and a problem called curse of dimensionality have been discovered. For example, the Kaplan-Meier which is a common nonparametric estimator has the following limitations: it is mainly descriptive, has no control for covariates, requires categorical predictors, and cannot accommodate time-dependent variables; it made no mathematical assumptions either about the underlying hazard function or about proportional hazard and nonparametric plots cannot be relied upon because, virtually all of them are unconditional .

1.2 Motivation

There is now a realisation that distributed lag models with normal error innovation are not efficient in modelling dynamic relationship between two or more variables and therefore there is need to develop distributed lag models with non-normal error innovation . It is also highly necessary to provide solution to the estimation problems under non-normality of the error distribution of the general form of distributed lag models i.e. there is need for an estimation process that is robust and insensitive to failure of underlying assumption. From the past works, as regards the case of violations of assumptions on general form of distributed lag models, a variety of statistical methods and model for correcting heteroscedasticity, non-linearity and multicollinearity are available but limited for non-normality of the error (Goldstein 1995), Maos and Hox (2013). Also very little attention has been paid to the convolution or mixed distribution from the distribution perspective of the error term because of the tedious and rigorous mathematics involved. So this work is to develop a conceptual frame work through which parameters of distributed lag model of the general form can be obtained that is robust to error assumption violation so as to improve on the descriptive and predictive status of a more versatile generalised model for skewed time series data.

1.3 Justification

The justification of this work based on literature review are highlighted as follows:

- The existing literature on robust distributed lag model of general form on error assumption violation is very scanty and limited.
- Violations of other assumptions has been considered in the literature but not the asymmetric error term of the general form of distributed lag model particularly from the distribution perspective.
- Non-parametric methods cannot adequately deal with skewed data and other related issues without not losing the originality of the data (Cleves *et al.* 2008)
- In case of severe violations of assumptions on distributed lag models, a variety of statistical methods and models for correcting heteroscedasticity, non-linearity and multicollinearity are available but limited for non-normality of the error (Goldstein 1995), Maos and Hox (2013).
- None of these authors considered exponentiated generalised normal distribution of the general form of distributed lag model with non-normality of the error distribution.

1.4 Significance of the Study

With the realisation that distributed lag models with normal error innovation are not efficient in modelling dynamic relationship between two or more variables, attempt will be made to develop a distributed lag model with non-normal error innovation to provide solution to the estimation problems under non-normality of the error distribution of general form of distributed lag model for time series data.

1.5 Aim and Objectives of the Study

The aim of this work is to develop a conceptual frame work through which parameters of distributed lag model of the general form can be obtained that is robust to violation of the assumptions of Normal error term. The objectives among others include:

(i) Development of the distribution lag models for both normal and non-normal error Innovations.

(ii) Estimation of parameters of the models with specified error term in (i)

(iii) Comparison of the models constructed in (i) with conventional distributed lag modeland

(iv) To make recommendations based on the well-known model selection criteria on theefficiency and suitability of the proposed model over the conventional model using both simulated and secondary data.

CHAPTER TWO

REVIEW OF LITERATURE

2.1 Literature Review on Distributed Lag Models

It was Fisher (1925) that first used and discussed the concept and application of a distributed lag, making use of time series data. In his later paper of (1937), he stated that the basic problem in applying the theory of distributed lags "is to find the 'best' distribution of lag, by which is meant the distribution such that the total combined effect (of the lagged values of the variables taken with a distributed lag has) the highest possible correlation with the actual statistical series with which we wish to compare it". The case of distributed lag model considered by Fisher was on lagging on the independent variable. In theory, distributed lags arise when any economic cause, such as a price change or an income change, produces its effect (for example, on the quantity demanded) only after some lag in time, so that the effect is not felt all at once at a single point in time but is distributed over a period of time. The Autoregressive Distributed Lag model (ADL) is the major workhorse in dynamic single-equation regressions. One particularly attractive re-parameterisation is the Error-Correction model (EC) and its popularity in applied time series econometrics has even increased; since it turned out for non-stationary variables that cointegration is equivalent to an error-correction mechanism (Engle and Granger, 1987). By differencing and forming a linear combination of the non-stationary data, all variables under consideration are transformed equivalently into an EC model with stationary series only. Working on feedback control mechanisms for stabilization policy, Phillips (1954, 1957) introduced EC models to economics. Sargan (1964) used them to estimate structural equations with autocorrelated residuals. According to Hylleberg and Mizon (1989) "the error correction formulation provides an excellent framework within which it is possible to apply both the data information and the information available from economic theory".

A survey on specification, estimation and testing of EC models is given by Alogoskous and Smith (1995). The paper contributes to this literature in that it treats some aspects of testing cointegration and asymptotic normal inference of the cointegrating vector estimated from an EC format. Most of the existing works are based on investigating the efficiency of various methods of estimating

DLM when the assumptions of homoscedasticity, no autocorrelation and no collinearity are jointly violated.

Distributed lag models in general find application whenever the influence of a time-indexed independent variable is delayed and spread over time. Although DLMs are widely applicable, their development was originally motivated by problems in econometrics (Nerlove et al. (1958), Almon (1965), Zellner and Geisel (1970), Haugh and Box (1977)) and have more recently experienced a surge in popularity in environmental epidemiology (Zanobetti, et al. (2010)). Crucially, DLMs enable direct interpretation of the influence of a temporal exposure ensemble, which is particularly useful for characterising the total health impact of persistent environmental exposures such as air pollution or temperature (Gasparrini et al. (2010) and Wyzga (1978). They concluded that lag models can help to identify subtle types of time-dependence such as 'mortality displacement', which occurs when exposure related mortality diminishes a vulnerable subpopulation, resulting in lower mortality in subsequent time intervals. Mortality displacement has been widely documented (Schwartz, 2000), Braga et al. (2001) and is conspicuous where lag influence is estimated to have a protective effect at low or moderate lags for what are otherwise harmful exposures (Zanobetti et al. 2000) only when the error term is assumed to be symmetric. Correctly identifying these effects depends on obtaining unbiased estimates of the underlying lag influence, and it is therefore essential that the DLM is correctly specified. It is however noted that here that emphasis is only on the model specification and not on normal error violation of DLM.

Mitchell *et al.* (1986) considered a case of a flexible DLM using polynomial inverse lag in a single autoregressive term in dependent variable. However, Gelles *et al.* (1989) extends the work of Mitchell *et al.* (1986) to include lag in explanatory variable in an approximation theorem for the polynomial inverse lag but assuming a normal error distribution.

In the work of Tiku, *et al.* (1999) they estimated parameters in DLMs but not of general form in non-normal error situations with Gamma distribution, and Generalised logistic and it was shown to be robust and efficient compared to Least Square Estimation. Shangodoyin, (2000) worked only on specification of DLM with outlier infested time series but also not of the general form of DLM.

Work on developing robust estimation of generalised linear models with measurement errors lagging only in explanatory variables was done by Li and Hsiao (2004), while Wong and Bian (2005) centered their own study on estimating parameters in autoregressive models with asymmetric innovations.

Keele and Kelly (2006) also only considered dynamic models for dynamic theories only on lagged independent variables in terms of existence of autocorrelation in the model. They however went on to use a Monte Carlo analysis to assess empirically how much bias is present when a lagged dependent variable is used under a wide variety of circumstances. In their analysis, they compare the performance of the lagged dependent variable model to several other time series models. It was concluded from their findings that while the lagged dependent variable is inappropriate in some circumstances, it remains an appropriate model for the dynamic theories often tested by applied analysts.

According to De Boef and Keele (2008) in their work, it was established that one can use a general specific modeling strategy to determine which restrictions, if any on DLMs, are appropriate and they use the results to calculate other quantities of interest, however there was no consideration of violation of basic assumptions on DLMs.

In the publication of Ozlem and Ayşen (2010) they considered a multiple autoregressive model with non-normal error distributions, this being more prevalent in practice than the usually assumed normal distribution. They worked out modified maximum likelihood equations by expressing the maximum likelihood equations in terms of ordered residuals and linearising intractable nonlinear functions and showed that for small sample sizes, they have negligible bias and are considerably more efficient than the traditional least squares estimators. They concluded that their estimators are robust to plausible deviations from an assumed distribution and are therefore enormously advantageous as compared to the least squares estimators. Crucially, distributed lag models enable direct interpretation of the influence of a temporal exposure ensemble, which is particularly useful for characterising the total health impact of persistent environmental exposures such as air pollution or temperature according to Gasparrini et al. (2010).

Ayinde et al (2012) only discussed in their work the performances of the LSE under the violations of assumption of non–stochastic regressors, independent regressors and error terms of linear regression while the work of Kgosi *et al.* (2013), was only based on specification of DLM in the presence of autocorrelated residuals**.**

Heaton and Peng (2014) in their work, modelled DLM to account for interactions between lagged predictors using Gaussian process. Their article proposes a new class of models, called high-degree DLMs, which extend basic DLM to incorporate hypothesised interactions between lagged predictors. The modelling strategy utilises Gaussian processes to counterbalance predictor collinearity and as a dimension reduction tool. To choose the degree and maximum lags used within the models, a computationally manageable model comparison method was proposed based on maximum a posteriori estimators. The models and methods were illustrated via simulation and application to investigating the effect of heat exposure on mortality in Los Angeles and New York. Adiele (2014) worked on estimation of linear distributed lag model that is heavily troubled only with autocorrelation.

Adewale *et al.* (2015) studied the relationship between expenditure and economic growth in Nigeria using a two stage robust autoregressive DLM approach which is not of general form of DLM. Maximum a-posteriori estimation of DLM processes based on infinite mixtures of scalemixtures of skew-normal distribution was worked on by Maleke and Arellano-Valle (2016). The form of DLM that was worked upon concerned only lagged dependent variables.

Ozbay and Kaciranlar (2017) introduced a Liu-type Shiller estimator to only deal with the problem of multicollinearity in DLM. They theoretically compare the predictive performance of the Liutype Shiller estimator with OLS and the Shiller estimators by the prediction mean square error criterion under the target function. Furthermore, an extensive Monte Carlo simulation study was carried out to evaluate the predictive performance of the Liu-type Shiller estimator.

Recent work contends that the lagged dependent variable specification is too problematic for use in most situations. More specifically, if residual autocorrelation is present and there is normal error violation, the lagged dependent variable causes the coefficients for explanatory variables to be biased downward. Bayesian adaptive distributed lag models according to Rushworth (2018) in his paper, showed that estimation of lag structure can strongly depend on the type of smoothing model that is assumed and that some several existing DLM models were shown to be non-robust to the choice of maximum lag p, even when the underlying lag function is identical, which suggests that the interpretation of lag estimates should be made with caution. A new model was developed that combines automatic adaptive smoothing with a pragmatically large choice of p to ensure simple and flexible smoothing of the lag curve that avoids sensitivity to the choice of p. The new approach provides users of DLMs with a new way to explore their data with confidence that the estimates are not contaminated by artefacts that resulted from particular model choices.

2.2. More about Distributed Lag Models

Generally, a distributed lag model can be defined as a model for time series in which a regression equation is used to predict current values of a dependent variable based on both the current values of an explanatory variable and the lagged (past) values of both the explanatory and dependent variables. Distributed lag models have been found to be very useful in various aspect of time series data.

2.2.1 The Role and Reasons of Lag in Economic Time Series

Generally in investigating relationship between two or more variables statistics, the effect of the explanatory variable on the outcome variable is hardly immediate, because most time the dependent variable react or respond to explanatory (independent) variable with a lapse of time and such a lapse of time is referred to as lag. In essence, the distributed as aspect of lag means, when effect do not occur immediately or instantaneously but are spread or distributed, over future time periods. For example, if income tax is increased, it will definitely affect disposable income, leading to reduction in expenditure, it will also affect the demand for goods and services, production will surely reduce, which will also affect profits of the manufacturers negatively and so on so forth. Therefore, a change effect in monetary and fiscal policy may take a while say eight to ten months before it's on economic outcomes can be so obvious.

There are many reasons that are adduce to the occurrence of lags in economic time series, but this can be easily classified into three:

a) **Psychological reasons:**

Generally as in human nature, people hardly change their consumption pattern or habit instantaneously if their income or salary increases or there is a downward trend in prices of goods and services because the process of change may involve some immediate disutility. For example, those who become instant millionaires by winning lotteries may not change the lifestyles to which they were accustomed for a long time because they may not know how to react to such a windfall gain immediately. Of course, given reasonable time, they may learn to live with their newly acquired fortune. Also, people may not know whether a change is "permanent" or "transitory." Thus, reaction to an increase in income will depend on whether or not the increase is permanent or temporary.

b) **Technological reasons.**

If for instance, the price of capital relative to labour declines, making substitution of capital for labour economically feasible, then of course, addition of capital takes time which can be referred to as the gestation period. Moreover, if the drop in price is expected to be temporary, firms may not rush to substitute capital for labour, especially if they expect that after the temporary drop the price of capital may increase beyond its previous level. Sometimes, imperfect knowledge also accounts for lags. For example, prospective buyers of handsets may have to hesitate to buy until they have had time to look into the features and prices of all the competing brands. Moreover, they may hesitate to buy in the expectation of further decline in price or new models.

c) **Institutional reasons.**

Another likely reason to the contribution of lag is the institutional reason. For example, contractual obligations may prevent firms from switching from one source of labour or raw material to another. Another example is the case of compulsory pension scheme introduced by Federal Government of Nigeria for all Federal civil servants since 2004, which is a case of institutional reason for lag, whereby money saved by members through various pension managers for a long period of time which are then fixed for the purpose of investment. The duration of fixing do range one year, two years, six years and even up to ten years. If there happens to be better alternative in the investment opportunity as a result improvement in the economy and the owner needs to move the fund to another investor since the pension scheme allow the civil servants the opportunity to change pension managers, this change cannot be effected until after a year, so therefore the employee is get stocked for at a least a year thereby resulting to lag.

For all the reasons stated above, it is very obvious that lags play a vital role in economic time series.

2.3 Different forms of Distributed Lag Models

There are different forms of distributed lag models. The various forms of it are discussed in this section.

2.3.1 Dynamic Model

A distributed-lag model also known as a dynamic model is a regression model in which the effect of explanatory or independent variables (x) on response or dependent variable (*y*) occurs over time rather than all at once. The point of emphasis here is that it is only lagged in the independent variable (x). Therefore in time series models, consideration is not only on how much effect the explanatory variable has on the outcome variable but when it has effect which is referred to as lag. There is also the question of whether the effect is immediate or is that it emerges slowly.

Now, the model for a situation of one dependent variable with assumption of linearity can be written as:

$$= \quad + \quad (\,) \quad + \quad = \quad + \sum \qquad + \qquad (2.1)$$

where is the value at time t of the dependent variable y, is the intercept to be estimated, is the white noise or the error term , ′s are the value at time t of the explanatory (independent) variables and ′ are the regression coefficients also to be estimated just like the classical regression model. The model of (2.1) has likely features of Autoregressive Moving Average model only, that the lag is not applicable to the error term but the explanatory variable. The above equation is a case of single distributed lag in the explanatory variable x.

2.3.2 Unrestricted Distributed Lags

In equation (2.1) if the effect of the explanatory variables on the outcome variable decays quickly, then the equation and the model coefficients to be easily and directly estimated using the method of LSE or GLS, however this is also with the assumption that the explanatory variable is strictly exogenous. This make the finite DLM advantageous over other type of distributed lag models. Finite distributed lags allow for the independent variable at a particular time to influence the dependent variable for only a finite number of periods. Therefore the interpretation of the model coefficients can be easily understood, however there are shortcomings of the finite distributed lag models, which can be classified into two. Firstly is when the explanatory variables are themselves correlated among each other which is referred to as mulicollinearity thereby leading to imprecise estimation; i.e., the standard errors tends to be large in relation to the estimated coefficients. As a result of this, based on the routinely computed test statistic t-ratio, we tend to declare wrongly that a lagged coefficient is statistically insignificant. The other disadvantage of this model is the presence of stochastic explanatory variables and the possibility of serial correlation most especially when the model do have elongated lag length. The presence of serial correlation do lead to not been able to apply the usual Chi-square , F-test and t-test even with fact that the time series is stationary that is if its characteristics which include the mean , covariance and variance do change over time.

2.3.3 Restricted Finite Distributed Lag Models

In equation (2.1) it is believed that the lag weights should be a smooth function of *s*. If the unrestricted finite distributed lag estimates contradict this smoothness, we may choose to restrict the model to impose smooth lag weights. Restricting the lag coefficients can not only impose smoothness, but also reduces the number of parameters that must be estimated. There are many patterns of smoothness that we can choose to impose a restrictive structure on the weights. One simple restriction on the lag weights is that they decline linearly from an initial positive or negative impact effect to zero at a lag of length $+ 1$. The where i = 1, 2, 3, ……….q are the lag weights for each coefficient are linearly decreasing ratios of the impact on the intercept as seen in table 1.1 constructed below. By the a constant value of $1/(1 +)$, makes the preceding value of to be lesser than individual lag weight until it decays to value 0 at the point of $= + 1$.

The lag weights formula is given and defined as:

(2.2) $= \underline{\qquad}$,

$= 1, 2, \ldots ,$

Table 1.1: Linearly Declining Lag Weights

Lag *s*	**Lag weight**
0	
1	$/(+\ \ )$
2	$(\ \ -/(\ +\ )$
…	**…**
$-$	$\mathbf{2}/(+\ \ )$
	$/(+\ \ )$
$+$	**0**

By substituting individual regression coefficient from equation (2.2) into equation (2.1) will lead to the estimation of linear decreasing lag model for a given value q.

$$= \ + \ \frac{q+1-s}{q+1} \ + \ = \ + \ \frac{q+1-s}{q+1} \ + \qquad (2.3)$$

For other shape of linear decreasing lag model the same step can be applied in the estimation the regression parameters. One of the commonest application of restricted distributed lag models is the polynomial DLM which was initiated by Almon (1965). The Almon technique assumes that β_i the regression coefficients can be approximated by a suitable-degree polynomial in i, the length of the lag. 49 for instance, if the lag scheme shown in broadly speaking, the theorem states that a finite closed interval any closed interval any continuous function may be approximated uniformly by a polynomial suitable degree.

A quadratic lag function restricts the lag coefficients to lie on a parabola:

$$= \quad + \quad + \quad , \quad = 1, \ldots , \quad , \tag{2.4}$$

where , , and are the parameters of the quadratic function describing the lag weights. Substituting into (2.1) yields

$$= \quad + \quad (\quad + \quad + \quad) \quad + \quad ,$$

$$= \quad + \quad + \quad + \quad +$$

or

$$= \quad + \quad + \quad + \quad + \quad , \tag{2.5}$$

where

$$\equiv \quad , \quad \equiv \quad \equiv$$

The *z* variables can be constructed by simple transformations once you have chosen a value of *q*, which allows equation (2.5) to be estimated by standard linear methods. Once we have obtained estimates for the parameters of (2.5), we can obtain the implied estimates of the lag weights from (2.4).

2.3.4 Models with Lagged Dependent Variables

In economic time series models, consideration is not only on how much effect the explanatory variable x has on the dependent variable y, but the time (lag) it has the effect. Then there is need to answer the two questions, firstly whether the effect is immediate and secondly whether the effect emerge gradually or slowly. For a univariate time series the autoregressive moving average (ARMA) time series process in which autoregressive (AR) is a component of the series allow the outcome (dependent) variable y_t to be explained by past or lagged values of the dependent variable itself and white noise process or stochastic error terms. Koyck lag is the commonest model of such, with one lag of the dependent variable and the explanatory variable on the right side of the equation.

2.3.5 Koyck Lag

The Koyck lag model assumes that the regression coefficients of the model are of the same sign and that they do decrease geometrically. For a lag model with one dependent variable and explanatory variable, this is represented by the equation;

$$= \quad + \qquad + \qquad + \qquad (2.6)$$

where is the dependent variable at time t, is the constant is the past value of dependent variable, and lag weights while is the error term that is assumed to be normally distributed.

Equation (2.6) can be expressed as

$$(1 - \qquad) \quad = \quad + \qquad =$$

in terms of the lag operator.

Therefore the solution for can be expressed as

$$= \text{———} \quad \text{———} x_i \quad \text{———} + \quad +$$

And by the similar process of AR this can be written in an infinite DLM form that gives

$$= \frac{}{1 -} + \qquad + \qquad (2.7)$$

as long as $| \quad | < 1$

Equation (2.7) has the form of the infinite distributed lag (2.6), with

$$= \text{——},$$

$$= \quad ,$$

and the error term will therefore have an infinite MA process. Therefore for the Koyck model, the effect of the explanatory variable on the dependent variable are given as

$$\text{——} = \quad = \quad , \qquad (2.8)$$

The long run effect of the explanatory variable on the dependent variable whenever the value of the coefficient lies between zero and one is

$$= \frac{}{1 -}$$

This exponentially declining lag distribution seems to fit many economic relationships well. Moreover, some theoretical models, such as exponential convergence models in economic growth and models with quadratic adjustment costs, predict exponentially declining lag weights.

The Koyck lag model can be used with more than one explanatory variable in the equation, but it imposes a significant restriction on the lag distributions. Suppose that we have two regressors, *x* and *z*:

$$= \quad + \qquad + \qquad + \qquad +$$

The dynamic marginal effects of *x* on *y* will be as in equation (2.8). The effects of *z* on *y*

will be

$$\underline{\qquad} =$$

For the Koyck lag model, as the value of s increases exponentially the effect of explanatory variable decreases which is not at the rate with the outcome variable, this is not however applicable in all situations. The theoretical and empirical appeal of the Koyck lag has led to its frequent use. However, consistent estimation of the Koyck-lag model can be problematic. The lagged dependent variable as an explanatory variable on the right-hand side is never strictly exogenous, so the smallsample assumptions needed for the Gauss-Markov Theorem cannot be satisfied. This is not however applicable to other distributed lag model of a autoregressive component of ARMA.

If the model of equation (2.6) is lagged once there is the possibility of the model to be correlated with the error term which is also lagged once. If however the error term is not random, the covariance of the lagged value of the error and the error term will not be a white noise, thereby making the lagged dependent variable and the error term to be weakly independent and the ordinary least square estimator to be inconsistent. For a given existence of autocorrelation in error term in the DLMs there will no longer be consistency in the estimation of Koyck model. In other to avoid the inconsistency in the estimation is to make sure the absence of serial correlation of the error term. However caution must be made in transforming the model into one that is not serially correlated by using generalised least squares method. Since the ordinary least squares estimators are consistently in consistent so also will be all the test statistic and estimators based on ordinary least squares error values.

2.3.6 Longer Autoregressive Lags

The dynamic model of Koyck lag treats the dependent variable as a first-order autoregressive (AP) process. Although lagging of the dependent variable once is often enough to capture the dynamic relationship between the dependent and the explanatory variables. However, longer autoregressive lags can be included as well. The general auto-regressive lag model of order *P* would be written

$$( ) \quad = \quad + \qquad + \quad , \tag{2.9}$$

where ( ) is a *p-order* polynomial in the lag operator. In order for the relationship between *y* and *x* to be dynamically stable, the roots of ( ) must lie outside the unit circle which is a necessary condition for stationarity of autoregressive model of order *P*. There will surely be a drastic change in the dependent variable when this is a onetime change in the explanatory variable if the stationary condition does not hold thereby leading to the process of differencing the dependent variable in other to make the order of integration on both sides of the equation equal. What actually determines the nature of the DLM distribution is the parameter of the AP lags. As with the first-order Koyck lag, lag weights can decrease smoothly according to an exponential pattern, however with a higher-order lags, there is the possibility of other nature of the model. For an illustration, when in a cyclical variation component in business, irregular variation may bring about shocks in productivity leading to marginal increase in the short run, thereafter decreasing and decaying or converging to zero in the long run.

2.3.7 Autoregressive Distributed Lag (ARDL) Models

The general form of an autoregressive DLM which allow a logical extension of lags on the right hand side of the equation in (2.9) is given as

$$( ) \quad = \quad + \quad ( ) \quad + \quad , \qquad (2.10)$$

where, is the explanatory variable at time t, ( ) is an order-*p* polynomial that, for stability, has roots lying outside the unit circle . By expanding the lag polynomials, equation (2.10) can be written as

$$= \quad + \qquad + \cdots + \qquad + \qquad + \cdots + \qquad +$$

The model can then be estimated given a sample size of n observations with maximum order (p,q).

Dividing both sides of equation (2.10) by the AR polynomial just like in autoregressive moving average models, we then have;

$$= \frac{}{( )} + \frac{( )}{( )} x_i + \frac{1}{( )}$$

$$= + \frac{\delta(L)}{\phi(L)} + \qquad (2.11)$$

Where v_i is the white noise process define in equation (2.11). The is sometimes being referred to as rational lag because of the fact that the lag distribution of autoregressive distributed lag model can be taken as the ratio of two finite lag polynomials. What makes a difference between the analysis of the autoregressive moving average distributed models and autoregressive distributed lag model is the lag structure in equation (2.11) that is not applicable to the explanatory variable but to the error term. Only the first lag of the dynamic lag distribution of the effect of explanatory variable on the outcome variable is affected by the coefficient of the order p polynomial just as in autoregressive moving average models. However the stability of the effect of the dynamic property is only feasible if and only if the root of the root of AR polynomial lie outside the unit circle and the nature of the lag distribution depends wholy on the AR polynomial beyond the order *p*.

2.3.8 Autocorrelated Errors and Distributed Lag Models

Making a distinction between the models in which the outcome variable *y* is autocorrelated and the models in which the white noise is autocorrelated is always not straight forward as regards estimation of the model parameters. Considering the autoregressive distributed lag model of order zero and one i.e. ARDL(1,0):

$$= \quad + \qquad + \qquad + \qquad (2.12)$$

and

$$= \qquad +$$

For stability and stationary it is assumed that the regression coefficients must lie between –1 and 1 for stability and stationarity and the error term is normally distributed. Solving for from the first line, $= \quad - \quad - \qquad -$, and at lag one will give;

$$= \qquad - \quad -$$

and substituting this into the second line and putting the resulting expression for into the first line gives:

$$= \quad + \qquad + \qquad + \quad (\qquad - \quad - \qquad\qquad - \qquad\qquad) +$$
$$= (1 - \quad) \quad + (\quad + \quad) \qquad - \qquad\qquad + \qquad - \qquad + \tag{2.13}$$

With first-order AR error autoregressive distributed lag model of order one and zero can be reduced to an autoregressive distributed lag model of order two and one as shown in equation (2.13). With the underlying parameters of , , and , therefore the autoregressive distributed lag model of order two and one in equation (2.13) can be estimated and test the nonlinear coefficient restriction as :

$$(\qquad) = \frac{(\quad)}{(\quad)} \qquad (\quad) - \frac{(\quad)}{(\quad)} \tag{2.14}$$

By imposing restriction on equation (2.14) as regards the estimation of the model in equation (2.13) or using the process of as outlined by Hildreth-Lu , then one d.f can be saved if the truly the model is a Koyck lag with autoregressive model of order one leading to the gaining of a significant efficiency. In not too a complex Koyck model i.e. simpler model, it is easier to estimate the unrestricted autoregressive distributed lag model of order two and one which accounts for the possibility of AR (1) error.

The illustration above indicates that by increasing the lag in autoregressive distributed lag model could possibly eliminate serial autocorrelation in the white noise process, it then means that the number of lags to be included in the model can then be easily determined. From the equation (2.13), if $= 0$ then the coefficients of both the explanatory variable and the explanatory variable at lags two and one respectively are both zeros, and if we need not to include the unwanted or unneeded autocorrelated errors is to test the last lag terms and eliminating them if they are near zero. Testing the residuals for autocorrelation should reveal whether the remaining error term is white noise. However, dealing with the possibility of autocorrelation or serial correlation in the disturbance, is by adding additional lags until the residual seems to be white noise which is the commonest practice by most time-series econometricians in recent times. Two-step general linear squares on using the Prais-Winsten or Hildreth-Lu procedures is used much less frequently

2.4 Summary of Different Forms of Distributed Lag Models

With the different forms of distributed lag models, this can be easily classified into the following forms;

a) Distributed lag models lagging both independent and dependent variables
b) Distributed lag models lagging only in dependent variable and
c) Distributed lag models lagging only independent variables.

In mathematical expression the distributed lag models take the following forms:

$$b + \quad + \quad + \qquad (2.15)$$

The equation (2.15) is a distributed lag model of a single distributed lag in X that is the model lagging only in independent variables.

$$b + \quad + \quad + \qquad (2.16)$$

The equation (2.16) is an autoregressive model which is a single autoregressive term in *Y* i.e. models lagging only in dependent variables.

$$b + \quad + \quad + \quad + \qquad (2.17)$$

The equation (2.17) is an autoregressive-distributed lag model, which in this case, is of order 1 in the autoregressive component and of order 1 in the distributed lag; this is often written as ARDL (1, 1) i.e. models lagging both in independent and dependent variables.

However, the general form of distributed lag model can then be expressed as:

$$= \quad + \sum \quad + \sum \quad + \qquad (2.18)$$

where is the value at time period *t* of the dependent variable, $\beta_{i,} = 1, . . ,$ and , $= 1, 2, ... ,$ are the lag weights to be estimated placed on the value *i* periods previously of the explanatory variable *x*, and is the error term and assumed to be normally distributed.

2.5. Choosing the Lag Length

The choice of appropriate lag length in all DLMs is very key in the estimation of its parameters.. In all forms of distributed lag models, before the estimation of the parameters of the specified model, it is very necessary that the length of the lag prior must be specified or determined. Theoretically, appropriate lag length cannot be determined but empirically. Though there has been different methods developed in the estimation or determination of appropriate lag length, they do not sometimes give the same result. There is no “right way” to identify the length of a lag (Gujarati and Sangeetha 2007). Most times with distributed lag model, forced judgment has to be made after looking at the evidence from several methods.

Application of some techniques for the choice of the right lag length is applicable to either to the lagged explanatory variable terms on the right-hand side, or to the number of lagged outcome variables to include in an AR lag or an ADLM. For the model such as linearly decreasing lag or polynomial distributed lag the straight method is not applicable to them since they are restricted types of lag model.

2.5.1 Determining Lag Length by Statistical Significance

For the statistical significance method of determine the appropriate lag length and gradually decreasing it successively by one period after the other until the null hypothesis cannot be rejected or statistically significant. This method however has its own shortcoming, because if an insignificant *t*- test statistic on the trailing lag fails to reject the hypothesis of a zero coefficient of the model this it does not actually prove that the coefficient is zero. Starting with a short lag length is therefore a possibility for this procedure and successively adding the lag term until the lag is statistically significant and this addition is stopped when the marginal coefficient is not statistically significant. The similarity of these two procedures described above may not always give the same choice of lag length. The reason why the methods in most times are not identical is the nonstatistically different form of the successive introduction in adding the lag.

2.5.2 Determining Lag Length by Information Criteria

In a set of explanatory variables what information criteria does about the outcome variable is to determine the quantity of information there in. Information criteria are goodness-of-fit measures of the same type just as coefficient of determination or adjusted coefficient of determination but without a simple interpretation as share of variance explained that we give to coefficient of determination in an ordinary least squares regression with an intercept term.. The Akaike information criterion and the Schwartz/Bayesian information criterion are the two most popularly and commonly used information criteria among the lot. The two information criteria are given and defined in log form as follows:

$$= In\ \left[\frac{\sum_{i-1}^{T}\hat{\mu}_i^2}{T}\right] + \frac{2K}{T}, \qquad (2.19)$$

and

$$= In\ \left[\frac{\sum_{i-1}^{T}\hat{\mu}_i^2}{T}\right] + \frac{K\ In\ T}{T}, \qquad (2.20)$$

From both equations (2.19) and (2.20) above ̂ are the error term and assumed to be normally distributed, k is the total number of the estimated coefficient of the parameters and T is the sample size. Just like the principle OLSE, the most important thing for the two type of information criteria is the minimization of the sum of square errors in order to choose the lag model with the smallest Akaike information criterion or the Schwartz/Bayesian information value.

However care must be taken when decision to make an appropriate choice of lag length using information criteria is to make sure that all models under consideration are put on exactly at the same sample period. Because of the fact that most often than not more observations are available for lag models with fewer lags resulting to the loss of smaller observations at the initial state of the sample. Using a different sample size for models with lags of different length will make the information criteria calculated for different models incomparable by allowing any statistical package such as statistical package for social sciences to set the initial sample size. Before confirming all the observations being compared that have similar sample lengths, the if or in conditionality in the estimation command must be used so as to keep the same sample across the models selected for comparison with either Akaike information criterion or the Schwartz/Bayesian information criteria value. Basically, there two terms that are common to both Akaike information criterion and the Schwartz/Bayesian information criterion. Firstly is the log of the standard error of the estimate with the uncorrected degree of freedom and secondly which measures to what extent of how the model best explained the outcome variable and secondly is the term the number of estimated parameters in which the term depends upon positively known as penalty term. By increasing the length of the lag will to the lowering of the first term by marginally improving the fit, however this will lead to the increase of the second term as a result of largeness in the number parameters has become. With this, both Akaike information criterion and the Schwartz/Bayesian information criterion provide alternative ways of "trading off" improved fit against more parameters to estimate.

2.5.3 Determining Lag Length by Residual Autocorrelation

As earlier mention in section 2.51, the addition of lags to the explanatory variable and or the dependent variable of the right hand side of the DLM regression will in most cases reduces the degree of the serial correlation in error term. Distributed lag models which in which its dependent variables are lagged has their estimators being sensitive to autocorrelated errors. Therefore, the alternative criterion to the choosing of the lag length is to eliminate the autocorrelation in the error terms. If the method of residual autocorrelation is being adopted in the determination of the length of the lag of DLMs the one needs to be adding the lag successively until the residuals becomes or appear to be white noise. When the DLM has been run and the residuals extracted, then a BreuschGodfrey LM test or a Box-Ljung *Q* test is used to test the null hypothesis that states that the residuals are white noise. More lag should be added to the model according to the criterion if the null hypothesis is however rejected.

2.6 Review on Extention of Some Exponentiated Distributions

In this section some of the works on expontiated distribution are going to be reviewed. In the work of Merovci and Elbatal (2015) they propose a new generalisation of exponentiated modified Weibull distribution, called the McDonald exponentiated modified Weibull distribution. This new distribution has a large number of well-known lifetime special sub-models such as the Beta exponentiated Weibull, McDonald exponentiated Weibull,exponentiated Weibull, exponentiated exponential, linear exponential distribution, generalized Rayleigh, among others. Some structural properties of this new distribution are studied, but however, they have never been used to model the general form of distributed lag model.

2.6.1 Exponentiated Weibull Distribution

For this distribution, its Probability Probability Density Function (P.d.f) for exponentiated Weibull distribution is defined by and considered in Mudhokar, et al., (1995) with parameter , and and life time has a density function as

$$(\ , \ , \ ) = \_\_ \ 1 - \exp(- \_ \qquad \_ -) \ ](-) \qquad (2.21)$$

Where > 0, > 0 are shape parameters and > 0 is a scale parameter.

It is a weibull distribution when $= 1$ and the exponential distribution when $= 1$ and $= 1$.

The survival function corresponding to random variable T with exponentiated-weibull density is given as

$$(; \ , \ , \ ) = \ (\ \geq \ ) = 1 - 1 - \exp(- \_ \qquad (2.22)$$

The greater flexibility of this model is in fitting survival data.

Then the maximum likelihood estimators of a three parameter exponentiated-weibull distribution is given as :

Let , , , ... , be a random sample from exponentiated-weibull the log likelihood can be as

(, ,) = , log —) + (− 1) log ( ) (/) + log(/) (2.23)

where

( ) = (; ,) = 1 − (− /)

We can differentiate (2.1) with respect to three parameters.

— = − + (− 1), ( )/ ( ) − (/) + log(/) = 0 (2.24)

— = − + log ( ) = 0 (2.25)

— = − — + (− 1) ( )/ ( ) + (/) (/) (2.26)

where

( ) = (−(/) (/) log(/))

( ) = − − exp (−(/)) — /

From (2.24), (2.25) and (2.26) the Maximum Likelihood Estimates (MLE) can then be obtained.

2.6.2 Exponentiated Exponential

The Probability density function of exponentiated exponential is defined by Gupta and Kunda (2001) with parameters and as

$$(, \quad , \quad) = \quad 1 - \qquad (2.27)$$

Where $\quad , \quad , \quad > 0$

Here is the shape parameter and is the scale parameter. When $= 1$, it represent the exponential family.

The survival function corresponding with exponentiated-exponential density is given as

$$(, \quad , \quad) = 1 - \quad 1 - \qquad (2.28)$$

The exponentiated exponential represents a parallel system.

Now, the maximum likelihood estimators of a two parameter exponentiated exponential distribution is as thus:

Let $\quad , \quad , \quad , \ldots ,$ be a random sample from exponentiated exponential the log likelihood can be as

$$(\; , \;) = \qquad + \qquad + (\quad - 1) \qquad (1 - \qquad) - \qquad (2.29)$$

Therefore, to obtain the MLE's of and we can directly maximize (2.29) with respect to and or we can solve the non-linear normal equations which are as follows:

$$— = ^{-} + \quad 1 - \quad = 0 \tag{2.30}$$

$$— = ^{-} + (\quad - 1) \quad \frac{}{1 -} \quad - \quad = 0 \tag{2.31}$$

From (2.24), we obtain the MLE of a as a function of , say ( ), as

$$( ) - \frac{}{\sum \quad (1 - \quad)}$$

If the scale parameter is known, the MLE of the shape parameter can be obtained directly from (2.26). If both the parameters are unknown, first the estimate of the scale parameter can be obtained by maximizing directly (( ).) with respect to . Once is obtained can be obtained from (2.26) as ( ).

2.6.3 Exponentiated Lognormal Distribution

The Probability density function (P.d.f) of exponential lognormal distribution is defined by with respect to the parameters (, ,) as :

$$; (\;,\; ,\;) \;=\; (\;(\quad ( ); \quad , \;)) \quad . (\;(\quad ( ); \quad , \;)) \tag{2.32}$$

$$, \quad > 0, -\infty < \quad < \infty$$

where (( ); ,)and (( ): 0 are the c.d.f and p.d.f of the normal distribution with mean and standard deviation as and .

The survival function corresponding with exponentiated lognormal distribution density is given as

$$(\, , \quad , \quad , \quad) = 1 - (\qquad (\,); \quad , \quad))$$

where $\quad > 0$

Now, for maximum likelihood estimators;

Let $\quad , \quad , \quad , \ldots ,$ be a random sample from Exponentiated lognormal distribution the log likelihood function can be as

$$(\, , \, , \quad / \,) = \qquad - \qquad (\quad) + (\quad - 1) \qquad (\quad); \quad , \quad) + \qquad (\quad); \quad , \quad) \qquad (2.33)$$

To find the values of the parameters , , that maximizes 1 (, , /) we can solve the equations which are as follows:

$$\frac{}{} = - + \qquad (\quad (\quad); \quad , \quad) = 0 \qquad (2.34)$$

$$\frac{}{} = (\quad - 1) \quad \frac{(\quad (\quad); \quad , \quad)}{(\quad (\quad); \quad , \quad)} + \quad \frac{(\quad (\quad); \quad , \quad)}{(\quad (\quad); \quad , \quad)} = 0 \qquad (2.35)$$

$$\frac{}{} = (\quad - 1) \quad \frac{(\quad (\quad); \quad , \quad)}{(\quad (\quad); \quad , \quad)} + \quad \frac{(\quad (\quad); \quad , \quad)}{(\quad (\quad); \quad , \quad)} = 0 \qquad (2.36)$$

From (2.34), (2.35) and (2.36) MLE of , and is obtained

2.6.4 Exponentiated Gumbel Distribution

The Probability density function (P.d.f) of Exponentiated Gumbel distribution was introduced by Nadarajah (2005) with parameters and as

$$(; \quad , \quad) = \_ \exp - \qquad (2.37)$$

where and > 0 $- \infty <$ $< \infty$

and is a shape parameter and is scale parameter.

Here when $= 1$ it reduces to standard Gumbel distribution

The survival function corresponding with Exponentiated-Gumbel density is given as

$$(, \quad , \quad) = 1 \_ \exp - \qquad (2.38)$$

The survival function of the Exponentiated Gumbel distribution is the the power of the survival function of the gumble distribution.

Its Maximum Likelihood Estimators as:

Let , , , ... , be a random sample from Exponentiated Gumbel distribution the log likelihood function can be as

$$(\; , \;) = \quad - \quad - \frac{1}{\_} \quad + \qquad (2.39)$$

Therefore to obtain the MLE's of and we can directly maximize (2.39) with respect to and or we can solve the non-linear normal equations which are as follows:

$$— = - + \qquad = 0 \qquad (2.40)$$

$$— = - + \frac{1}{} \qquad - \_\_ \qquad = 0 \qquad (2.41)$$

From (2.40) and (2.41) maximum likelihood estimates of and is obtained.

2.7 Gaps in Literature

From the review of literature and in connection with this research work some of the gaps identified are highlighted in this section**.**

- Fisher (1937). Introduced an alternative short-cut method for the estimation of parameters of distributed lag models but lagging only in independent variables.
- Mitchell *et al.* (1986). Considered a case of a flexible DLM using polynomial inverse lag in a single autoregressive term in Y.
- Gelles *et al.* (1989). Extends the work of Mitchell *et al.* (1986) to include lag in explanatory variable in an approximation theorem for the polynomial inverse lag.
- Tiku, M.L. *et al.* (1999). Estimated parameters in DLMs (not of general form) in nonnormal error situations with two distributions, Gamma and Generalised logistic, it was shown to be robust and efficient compared to Least Square Estimation.

- Shangodoyin (2000). Worked only on specification of DLM with outlier infested time series and also not of the general form of DLM.

- Li and Hsiao (2004) work was on developing robust estimation of generalised linear models with measurement errors lagging only in explanatory variables.

- Wong and Bian (2005). Centered their study on estimating parameters in autoregressive models with asymmetric innovations.

- Keele and Kelly (2006).Considered dynamic models for dynamic theories only on lagged independent variables.

- Ayinde *et al.* (2012). Discussed in their work the performances of the LSE under the violations of assumption of non–stochastic regressors, independent regressors and error terms of linear regression.

- Kgosi *et al.* (2013). Their worked was only based on specification of DLM in the presence of autocorrelated residuals**.**

- Heaton and Peng (2014). In their own work, they modeled DLM to account for interactions between lagged predictors using Gaussian process.

- Adiele F.D (2014). Worked on Estimation of Linear DLM that is heavily troubled with only Autocorrelation.

- Adewale *et al.* (2015). Studied the relationship between expenditure and economic growth in Nigeria using a two stage robust autoregressive DLM approach which is not of general form of DLM.

- Maleke and Arellano-Valle (2016). Considered maximum a-posteriori estimation of DLM processes based on infinite mixtures of scale-mixtures of skew-normal distribution.

- Ozbay and Kaciranlar (2017). Introduced a Liu-type Shiller estimator to only deal with the problem of multicollinearity in DLM.

In summary, the existing literature on robust distributed lag models on error assumption violation is very scanty and limited. In case of severe violations of assumptions on distributed lag models, varieties of statistical methods and model for correcting heteroscedasticity, non-linearity and multicollinearity are available but limited for non-normality of the error, (Goldstein 1995), Maos and Hox (2013). None of these authors considered Exponentiated generalised normal distribution of the general form of DLM with non-normality of the error distribution. Therefore this research is to develop a robust DLM of general form under non-normality of the error distribution.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

Estimation of the coefficients in distributed lag models is one of the most important aspect of time series analysis and it has received tremendous attention in the literature. Most of the work reported are, however, based on the assumption of normality of the error term. In recent years, however, it has been recognised that the underlying distribution is, in most situations, basically not normal, especially in time series data. The solution, therefore, is to develop efficient estimators of coefficients in distributed lag model when the underlying distribution is non-normal.

3.2 Distributed Lag Models

A distributed lag model is a special case of regression for time series data in which a regression equation is used to predict current values of a dependent variable based on both the current values of an independent variable and the lagged (past period) values of this independent or explanatory variable. Distributed lag models are also referred to as dynamic models because they contain lagged values of variables, as well as current-dated ones that is looking at the effect of explanatory variable on the dependent variable over time. Generally, distributed lag models are used in time series in order to investigate causal relationship between input and output series. The distributed lag models have been found to very use full in many areas of statistics and other fields such as in Economics (Gomez 2009),Biological Sciences (Harvey, 1989) and Statistical Process Control (Box and Jenkins, 1976). More about distributed lag models are discussed in the literature review section.

3.2.1 Basic Assumptions underlying Distributed Lag Models

Basically, there are four principal assumptions which justify the use of most regression models for purposes of inference or prediction and distributed lag model is not an exemption. These assumptions are considered below:

(a) Linearity and additivity of the relationship between dependent and independent variables: the implication of this assumption are:

(i) The expected value of dependent variable is a straight-line function of each independentvariable, holding the others fixed.

(ii) The slope of that line does not depend on the values of the other variables.

(iii) The effects of different independent variables on the expected value of the dependent variableare additive.

(b) Statistical independence of the errors implies, no correlation between consecutive errors in the case of time series data. When the assumption of independence of error terms is violated as it is often found in time series data, the problem of autocorrelation arises. Several authors have worked on this violation especially in terms of the parameter estimation of the linear regression model when the error term follows autoregressive of orders one. The OLS estimator is inefficient even though unbiased. Its predicted values are also inefficient and the sampling variances of the autocorrelated error terms are known to be underestimated causing the Student-t and the F tests to be invalid.

(c) **Homoscedasticity** implies that the variance error term is constant variance of the errors. One instance in which robust estimation should be considered is when there is a strong suspicion of heteroscedasticity. In the homoscedastic model, it is assumed that the variance of the error term is constant for all values of the variables.

(d) **Normality** of the distribution error term.

If any of these assumptions is violated i.e., if there are nonlinear relationships between dependent and independent variables or the errors exhibit correlation, heteroscedasticity, or non-normality, then the forecasts, confidence intervals, and scientific insights yielded by the regression model may be (at best) inefficient or (at worst) seriously biased or misleading.

3.3 Violation of Assumptions

Generally, violations of normality assumptions create problems for determining whether model coefficients are significantly different from zero and for calculating confidence intervals for forecasts and distributed lag models are not excluded. Sometimes the error distribution is "skewed" by the presence of a few large outliers. Since parameter estimation is based on the minimization of squared error, a few extreme observations can exert a disproportionate influence on parameter estimates. Calculation of confidence intervals and various significance tests for coefficients are all based on the assumptions of normally distributed errors. If the error distribution is significantly non-normal, confidence intervals may be too wide or too narrow, this is also applicable to distributed lag models. Technically, it is believed that the normal distribution assumption is not necessary if you are willing to assume the model equation is correct and your only goal is to estimate its coefficients and generate predictions in such a way as to minimize mean squared error. The formula for estimating coefficients require no more than that, and some references on regression analysis do not list normally distributed errors among the key assumptions. We know that generally interest is in making inferences about the model and or estimating the probability that a given forecast error will exceed some threshold or value in a particular direction, in which case distributional assumptions are important. Also, a significant violation of the normal distribution assumption is often a "red flag" indicating that there is some other problem with the model assumptions and/or that there are a few unusual data points that should be studied closely and/or that a better model is still waiting out there somewhere.

From literature review, robust distributed lag model of the general form with asymmetric error term has not been thoroughly studied. This work intent to fill this gap. Therefore, this study is focused on developing a robust distributed lag model that would be insensitive to normal error assumption violation.

3.4 Robust Statistics

There are various definitions of a robust statistic. Strictly speaking, a robust statistic is resistant to errors in the results, produced by deviations from assumptions (Frank et al 2005). Robust statistics, therefore, are any statistics that yield good performance when data is drawn from a wide range of probability distributions that are largely unaffected by outliers or small departures from model assumptions in a given dataset. In other words, a robust statistic is resistant to errors or outliers in the results. The implication of this is that, if the assumptions are only approximately met, the robust estimator will still have a reasonable efficiency, and reasonably small bias, as well as being asymptotically unbiased, that is, having a bias tending towards zero as the sample size tends towards infinity.

One of the most special cases is distributional robustness. Classical statistical procedures are typically sensitive to "longtailedness" for example when the distribution of the data has longer tails than the assumed normal distribution. Therefore, in the context of robust statistics, distributionally robust and outlier-resistant are effectively synonymous.

For the methodology, a conceptual framework is developed through which parameters of the DLMs can be obtained in the presence of normal error assumption violation. The DLMs both for the normal and non-normal error innovations will be specifiedand parameters of the DLMs with both normal error and non-normal innovation will then be estimated. Exponentiated Generalised Normal Distribution (EGND) is used to model the general form of DLM and method of Maximum Likelihood Estimation (MLE) will be used in estimating the parameters of the model.

Attempts is also made to derive the functional form of the distribution and determine some statistical properties of the developed model.

The estimation of the parameters will be made from both the Exponentiated generalised normal distribution and normal distribution using the method of maximum likelihood estimation. The fisher's information matrix and variance of each of the parameter will be obtained, so as to be able carry out inference on parameters of the model which include the construction of confidence intervals and test of hypothesis.

3.5 Gaussian Distribution

Gaussian distribution otherwise known as the normal distribution has proved the most useful of all distributions for continuous random variables. The normal distribution function for a random variable is given by ( )

$$(X) = \frac{1}{\sigma\sqrt{2\pi}} \epsilon^{-\frac{}{2\sigma^2}} \qquad (3.1)$$

where $-\infty <$ $< \infty$ >0

This shows that a normal distribution is completely determined by specifying its mean and standard deviation , also the graph of a typical normal curve is symmetrical about the mean .

The maximum likelihood estimate of the parameters of a normal distribution can be obtained by the likelihood function.

$$(\ ) = \prod \quad (\ ,\ ) \qquad (3.2)$$

where $\ ,\ = 1, 2, \ldots,$ are random samples from a population X with the probability density function $F(X, \theta)$ and θ is an unknown parameter.

The probability function (3.2) can be expressed as

$$(\ ,\ ,\ ) = \frac{1}{\sigma\sqrt{2\pi}} \ell^{-\overline{2\sigma^2}} (\ ),$$

where $-\infty < \quad < \infty \qquad > 0$

The likelihood function is

$$(\ ,\ ) = (2\ )_{-} \exp[- \_\_ (\ -\ )\ ]$$

then the log likelihood function

$$\text{In} \ = - \quad (\ ) - \_\_ \sum(\ -\ ) \qquad (3.3)$$

The maximum likelihood estimate of the population mean can be obtained by differentiating equation (3.3) with respect to μ and equate to zero.

$$\frac{(\ ,\ )}{} = - \_\_ \sum(\ -\ ) = 0 \qquad (3.4)$$

$$= \frac{\sum x_i}{n} \qquad (3.5)$$

The maximum likelihood estimate the variance is obtained by differentiating (3.3) with respect to and equating the result to zero.

We have,

$$\frac{(\; , \quad)}{} = - \frac{}{} - \frac{}{} \sum(\quad - \quad) \quad = 0$$

$$\frac{}{} = \sum \frac{(\qquad)}{}$$

$$\text{n} \quad = \sum(\quad - \quad) \qquad (3.6)$$

That is $\sim \; (\, , \quad)$

Factorial Moment of Normal Distribution

$$= \int \; (\quad -) \qquad ( )$$

$$= \frac{1}{\sigma\sqrt{2\pi}} = \int_{-\infty}^{\infty} (y - \mu) \qquad \frac{}{}$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\sigma z) \qquad \frac{}{} \qquad = \frac{}{}]$$

$$= \frac{\sigma^{2n+1}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \qquad \frac{}{}$$

$= \; 0$ (since $\frac{}{}$ is an odd function)

$$= \int_{-\infty} (y - \mu)^{2n} f(y)$$

$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\sigma^2 z) \quad - \quad = \frac{\sigma^{2n}}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} \quad -$

(— is an even function)

$= \frac{2^n \sigma^{2n}}{\sqrt{\pi}} \int_0^{+\infty} \quad - \_$

$= \frac{2^n \sigma^{2n}}{\sqrt{\pi}} \quad + \_$

Changing n to (n-1) we get

$= \frac{\qquad}{(\ )} \quad - \_$

On dividing, we get

$\_\_\_ = 2 \quad \frac{\Gamma\left(\pi + \frac{}{2}\right)}{\Gamma\left(\pi - \frac{1}{}\right)} = \frac{2\ \sigma\ \left(n - \frac{}{2}\right)\Gamma\left(\pi - \frac{}{2}\right)}{\Gamma\left(\pi - \frac{1}{}\right)}$

$= 2 \quad - \_$

$= \quad (2 \quad - 1)$

which gives the recurrence relation for the moments of normal distribution

$= [(2 \quad - 1)][(2 \quad - 3) \quad]$

$= [(2 \quad - 1) \quad][(2 - 3) \quad][(2 \quad - 5) \quad]$

$= [(2 \quad - 1) \quad][(2 \quad - 3) \quad][(2 \quad - 5) \quad] - 3\ (3 \quad)(1 - \quad)$

$= (2 \quad - 1)(2 - 3)(2 \quad - 5) - 1.$

=1.3.5.7… (2n -5) (2n-3) (2n -1)

3.6 Specifying and Estimation of the Parameters of Distributed Lag Model with Normal Error Innovation

The general form of distributed lag model is specified as :

$$= \quad + \sum \qquad + \sum \qquad + \qquad (3.7)$$

where is the value at time period *t* of the dependent variable, is the intercept ,

$\beta_{i,}$($= 1, \ldots ,$) and , $= 1, 2, \ldots ,$ are the lag weights to be estimated placed on the

value *i* periods previously of the explanatory variable *X* and dependent variable *Y* respectively,

and is the error term and assumed to be normally distributed**.**

Now, if is assumed to follow a normal distribution i.e. ∽ , ,

Then the probability distribution function of Y_t is given as

$$(y_t) = \frac{1}{\sqrt{2\pi\sigma^2}} \quad -(\qquad (3.8)$$

where $-\infty <$ $< \infty$ >0

Putting (3.7) into (3.8) we have

$$(y_t) = \frac{1}{\sqrt{2\pi\sigma^2}} \quad - \quad + \quad + \qquad (3.9)$$

Taking the likelihood of (3), we have

$$(\quad) = (2 \qquad)^{-\ -\frac{}{2}} \quad - \quad + \qquad + \tag{3.10}$$

Now by taking the Log likelihood of (4) and denoted by m, we have

$$= \qquad (\quad) = -\frac{}{2}\log 2 \qquad -\frac{1}{2} \qquad - \quad - \tag{3.11}$$

Now by differentiating (3.11) with respect to: , , and respectively gives

$$\frac{}{} = \frac{1}{} \qquad - \quad - \tag{3.12}$$

$$\frac{}{} = \frac{1}{} \qquad - \quad - \tag{3.13}$$

$$\frac{}{} = \frac{1}{} \qquad - \quad - \tag{3.14}$$

$$\frac{}{} = \frac{-}{} + \frac{1}{} \qquad - \quad - \tag{3.15}$$

The estimate of the parameters are in close form, hence it can be obtained by numerical methods.

3.6.1 Fisher Information Matrix DLM with Normal Error Term

The Fisher's Information Matrix (FIM) is a very useful tool for calculating the interval estimates of parameters, asymptotic variances, covariance and for testing hypothesis of *β_0, βi, and α_j* .

The Fisher's information matrix are now obtained as follows:

Now, taking the second derivatives of (3.12), (3.13), (3.14), and (3.15) respectively we have:

$$= \quad 1 \quad - \quad - \qquad (3.16)$$

$$= \quad [\quad \Sigma \quad - \Sigma \quad - \Sigma \quad \Sigma \quad \Sigma$$

$$= \qquad (3.17)$$

$$= \quad 1 \quad - \quad - \qquad (3.18)$$

$$[\quad 1 \quad =- \quad -$$

$$= \quad -1 \qquad (3.19)$$

$$\frac{\quad}{\quad} \quad \frac{\quad}{\quad}\left[\frac{\quad}{\quad} \quad 1 \quad = \quad -\right] \tag{3.20}$$

$$\frac{\quad}{\quad}\left[\frac{\quad}{\quad} \quad 1 \quad - \quad - = \quad \frac{\quad}{\quad}\sum\right] \tag{3.21}$$

3.6.2 Cramer-Rao Variance

Cramer-Rao variance is the inverse of the element of Fisher Information Matrix, which is necessary for statistical inference on the parameters, hence the variance of the estimate of the parameters are the diagonal elements of the matrix:

$$= \frac{\quad}{\quad} \tag{3.22}$$

$$= \frac{\sigma}{\sum_{t=1}^{n} X_{t-i}^{2}} \qquad = 1, 2, \dots, \tag{3.23}$$

$$= \frac{\quad}{\sum} \qquad = 1, 2, \dots, \tag{3.24}$$

3.6.3 Interval Estimation of the Parameter for DLM with Normal Error Term

From the estimates of DLM parameters and their variances obtained above, the interval estimates of the parameter can be obtained using the estimates and their corresponding variances. The confidence intervals for , and are

(i) $\pm \,, \quad 2 \quad \sqrt{\quad}$ (3.25)

(ii) $\pm \,, \quad 2 \quad \sqrt{\quad}$, 1, 2, ... , (3.26)

(iii) $\pm \,, \quad 2 \quad \sqrt{\quad}$ = 1, 2, ... (3.27)

3.7 Proposed Model

In this section, the proposed model for error distribution will be specified, developed and the process of estimating its parameters will be well detailed.

3.7.1 Specifying and Estimation of the Parameters of Distributed Lag Model with Non Normal Error Innovation

Since there is a violation of the normality assumption of the error or residual term of the general form of distributed lag model, a non-normality in terms of the distribution of the error term on DLM will be specified made so that whatsoever the estimation of the parameter that will be made will now be made from non-normality distribution perspective of the error term. This is the reason why the normal distribution of the error term which is symmetric in nature and by the use of Exponentiated link that is asymmetric, the normal distribution is convoluted with Exponentiated link function which will be referred to as Exponentiated Generalised normal distribution. The resulting model that is non normal and is asymmetric in nature. This is the distribution that will be used to model the distributed lag model with violation of assumptions. The performance will be compared with the DLM with normal distribution.

3.7.2 Model Specification

This study used the Exponentiated generalised link function by Gupta et. al. (1998) and extended by Rager and Mir (2011). The error innovation is assumed to follow the Exponentiated Generalized Normal Distribution.

Let y be the random variable, then the assumed link function is given as:

$$( ) = \quad ( ) \quad ( ) \tag{3.28}$$

where >0 and is the shape parameter and

( ) is the conventional normal distribution i.e.

$$(y) = \frac{1}{\sqrt{2\pi\sigma^2}} \quad -(\text{—}) \tag{3.29}$$

where $-\infty <$ $< \infty$, $-\infty <$ $< \infty$ and > 0

and *F(y)* is the corresponding cumulative density function of the normal distribution and giving as

$$( ) = \quad \text{—} \tag{3.30}$$

Now, by substituting (3.29) and (3.30) into (3.28) to have the Exponentiated generalised normal distribution given as

$$( ) = \quad \frac{-}{} \quad \frac{1}{\sqrt{2\pi\sigma^2}} \quad -(\text{—} \tag{3.31}$$

which is now the Exponentiated generalised normal distribution.

3.7.3 Properties of Exponentiated Generalised Normal Distribution

There is need to verify whether the proposed distribution is of proper distribution.

For a proper pdf it is required that $\int \quad ( ) \quad = 1$

Then, from equation (3.31)

$$( ) \quad = \quad \phi \frac{-}{\quad} \quad \frac{1}{\sqrt{2\pi\sigma^2}} \quad -(\text{—} \quad \text{dy}$$

Now, if we let

$= \phi \text{—}$ Then,

$$\text{—} \quad = \frac{1}{\sqrt{2\pi\sigma^2}} \quad -(\text{—})$$

Then

$$= \frac{\sqrt{2\pi\sigma^2}}{{}^{1}\left(^{y \quad \mu}\right)^{2} -(\text{—})}$$

Now,

$$\begin{array}{c} 1 \\ ( ) \end{array} \quad = \quad \frac{}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2} \frac{\sqrt{2\pi\sigma^2}}{e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}}$$

$= \quad \int$

$= \quad \_\, 1 = \quad 1$
$\quad\; 0 \qquad 0$

$= (1) \quad - 0$

$$= 1$$

This verified that Exponentiated Generalised normal is a proper probability distribution function.

3.7.4 Parameter Estimation of the proposed Model

For a given distributed lag model of the general form;

$$= \quad + \quad + \quad + \tag{3.32}$$

where is the value at time period *t* of the dependent variable, is the intercept ,

$\beta_{i,}$($= 1, \ldots ,$) and , $= 1, 2, \ldots ,$ are the lag weights to be estimated placed on the

value *i* periods previously of the explanatory variable *X* and dependent variable *Y* respectively,

and is the error term and assumed to be normally distributed**.**

We can then now substitute equation (3.32) into (3.31) to have:

$$(\quad) = \quad \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\frac{\left(y-\beta_o-\sum_{i=1}^{\rho}\beta_i X_{t-i}+\sum_{j=1}^{q}\alpha_j Y_{t-j}\right)}{\sigma^2}} \qquad (3.33)$$

As the pdf of the general form of the DLM variable

3.7.5 Parameter Estimation

Using log likelihood functions of EGND equation 3.33 at a baseline distribution, the parameters , , of the model can be estimated by differentiating it with respect to the parameters.

The likelihood function of (3.33) is

$\prod \quad (\quad) =$

$\prod \quad (2 \quad)^{-} \quad \sum \quad - \quad -\sum \quad -\sum$ (3.34)

Now taking the log of (3.34), we have the log likelihood function as

$= \quad + (\quad - 1) \quad) \quad - \quad 2 \quad - \quad 2$

$\frac{1}{2\sigma^2} \quad -$

$-- \quad - \quad +$ (3.35)

Differentiating (3.35), with respect to , , , we have

$$- = - \quad + \sum \qquad (3.36)$$

$$- = (\quad - \quad -)] \quad - \quad - 1)\sum \quad + \qquad (3.37)$$

$$- \quad \frac{1}{2\sigma^2} \quad = - \quad - \quad + \qquad (3.38)$$

$$- \quad \frac{1}{2\sigma^2} \quad = - \quad - \quad + \qquad (3.39)$$

There is no close form solution for the estimates and has to be obtained by numerical analysis.

3.7.6 Fisher Information with Non-Normal Error Term for DLM

In other to obtain the elements of Fisher Information, equations (3.36), (3.37), (3.38), and (3.39) are again differentiated to have:

$$- = - - \qquad (3.40)$$

$$\frac{}{(\quad)} = (\quad \overset{-}{} - 1) - \quad -)\Big] \quad - \quad - \qquad (3.41)$$

$$- = - \sum \quad \sum \qquad (3.42)$$

$$\_\_\_ = \frac{-1}{2\sigma^2} \quad (3.43)$$

3.7.7 The Cramer-Rao Variance

The Cramer-Rao variance which is the reciprocal is used in statistical inferences to obtain interval estimation and conducting hypothesis testing on the parameter under consideration.

The respective variances of the estimated parameters for the DLM with non-normal error term are:

$$= \overline{\frac{\partial^2 l}{2}} \quad \overline{(\sum_{i=1}^{q} Y_{t-j})(\sum_{i=1}^{q} Y_{t-j})} = \quad (3.44)$$

$$(\quad) = \overline{\frac{\partial^2 l}{2}} \quad \overline{(\sum_{i=1}^{\rho} X_{t-i})(\sum_{i=1}^{\rho} X_{t-i})} = \quad (3.45)$$

$$() = \overline{\frac{\partial^2 l}{}} \quad \overline{n^2} = \quad (3.46)$$

$$(\ ) = \overline{\frac{\partial^2 l}{\partial \sigma^4}} \quad \overline{(\alpha-1)\frac{\partial^2}{\partial \sigma^2}\left[\sum_{t=1}^{n} log\phi\left(\frac{y_t-\mu}{\sigma}\right)\right] - \frac{n}{\sigma^2}} = \quad (3.47)$$

3.7. 8 Interval Estimation for the Parameters of the DLM with Non-normal Error Term

The confidence intervals for each of the parameters of the model are also required in the aspect of inferential statistics. These are given as:

For α we have, $\pm \quad / \quad (\ )\sqrt{}$

For β we have; $\pm \quad / \sqrt{}$

For we have; $\pm \quad /\sqrt{} \quad (\ )$

3.7.9 Hypothesis Testing

For θ we have ; $\pm \quad /$ and $\sqrt{}$ In other to be able to test for all possible hypotheses for the significance of model, the appropriate test statistic for the parameters of the DLM with non-normal error term are defined as follows:

$$(1) \qquad : \ = 0 \quad : \quad \neq 0$$

$$= \sqrt{} \qquad = 1, 2, \ldots$$

$$(2) \qquad : \ = 0 \quad : \quad \neq 0$$

$$= \sqrt{} \qquad = 1, 2, \ldots$$

$$(3) \qquad : \ = 1 \quad : \quad \neq 1$$

$$= \quad ( ) \quad \sqrt{}$$

CHAPTER FOUR

DATA ANALYSIS AND RESULTS

4.1 Introduction

In this chapter, the analysis of data, which include exploratory data analysis, charts and figures that represent what the study entails are presented. For the validation of the proposed model both real (secondary) data and simulated data were made use of in order to achieve the set objectives of this research.

4.1.1 Real Data used.

Monthly data on Nigeria's Gross Domestic Product (GDP) and External Reserves (ER) that span from 1981 to 2015 were made use of for the analysis. These were extracted from the Central Bank of Nigeria (CBN) statistical bulletin (2016). The GDP was used as the dependent variable (y) while the external reserve was used as the explanatory variable (x). The real data were subjected to exploratory data analysis in order to confirm the skewedness of the data by constructing appropriate graphs and test statistics before the proposed model can be applied to secondary data.

4.1.2 Simulated Data

Two different sets of simulated data are considered. The first case is a situation with normal data with normal error term and the second scenario is a skewed data with non-normal error term. In each case a varying sample sizes of 20, 50, 200, 500, 1000, 5000 and 10,000 of simulated were used. And in order to ensure the stability of the estimates, each simulated data were replicated 10,000 times in other to examine the consistency of the estimated parameters of the models.

4.1.3 Procedure for Monte Carlos Simulation

The step by step procedure for the simulation are stated below.

- Two simulation criteria as earlier stated are used:
  - When the error term is assumed to be normally distributed and
  - When the data is skewed or error term is assumed not to be normally distributed or skewed.

- For each criteria, samples of sizes 20, 50, 200, 500, 1000, 5000 and 10,000 respectively were simulated.

- In order to ensure that the data is well-skewed, for this work, exponential distribution was used to simulate non-normal data because it exhibits clearly non-normality of data.

- The two models Normal and EGND were fitted on the data generated in the following way:

- By obtaining or simulating a variable ((−) by generating forexample

  ~ exponential, error ~ normal for and when it is asymmetric.

- Since the distributed lag model has were lagged, the variable was also generated in a similar manner.

- Thus, each model were formed and fitted using the generated data.

- Criterion statistics of AIC, BIC, CAIC and HQIC were obtained to establish the better model.

- Replication on these estimates were done 10,000 times for all samples and the mean of the replicates on which we compute the absolute bias were obtained. All simulations were carried out using R.codes.

4.2 Model Selection

Model selection in statistics generally refers to the problem of using the data to select one model from the list of competing models. It also involves the use of a model selection criterion to finding the best fitting model to the data (Wasserman, 2000). Model selection using information criteria is used to summarise data evidence in favour of a model. Meanwhile, information criteria techniques emphasised minimising the amount of information required to express the data and model. To select the best model out of a lot can be very dicey, that is why it is usually advised that not just one criterion should be used but if possible an array of criteria. This leads to selection of models that constitute an efficient representation of both the real data and simulated data.

Therefore fore this research work, information criteria was employed in this study to select the most appropriate model between the developed and competing model based on the model with consistently lower values. In this regard relevant traditional information-theoretic criteria which include Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Schwarz, 1978); and lesser-known criteria such as Consistent Akaike Information Criterion (CAIC) and Hannan Quinne Information criteria (HQIC) which have been used for the purpose of identifying the correct asymmetric model and address model selection problems.

4.2.1 Akaike Information Criterion (AIC)

Akaike Information Criterion is one of the first model selection methods introduced by Akaike in 1973 and it is also the most commonly used information criterion. AIC is an estimator of the relative quality of statistical models for a given data. AIC is based on the idea that a chosen model is correct if it can sufficiently describe any future data with the same distribution and therefore AIC can be regarded as a hypothetical cross validation method (Acquah, 2013). It selects a model that minimises the expected error of the new observation with the same distribution as the data used for fitting the model. AIC is a bit more liberal often favours a more complex, wrong model over a simple, true model. Thus, AIC provides a means for model selection. It is defined as:

$$\mathrm{AIC} = -2\mathrm{LogLik} + 2\ \mathrm{r}$$

where is the likelihood under the fitted model and

r is the number of parameters in the model.

The model with minimum AIC value is chosen to be the best model among competing models. More importantly, AIC is aimed at finding the best approximating model to the unknown true data generating process and its applications.

4.2.2 Bayesian Information Criterion (BIC)

Bayesian information criterion is another widely used information criterion. Unlike Akaike Information Criterion, BIC is derived within a Bayesian framework as an estimate of the Bayes factor for two competing models (Schwarz, 1978; Kass and Rafftery, 1995). Thus, BIC is defined as:

$$\mathrm{BIC} = -2\mathrm{LogLik} + \mathrm{r}\ (\mathrm{Log}\ \mathrm{n})$$

where LogLik refers to the likelihood under the fitted model,

r is the number of parameters in the model and Log (n) is the logarithm of n , while n is the sample size.

Automatically, BIC differs from AIC only in the second term which now depends on sample size n. Models that minimise the Bayesian Information Criteria are selected. BIC is designed to identify the true model while AIC does not depend directly on sample size. Bozdogan, (1987) noted that because of this, AIC lacks certain properties of asymptotic consistency. From a Bayesian perspective, BIC is designed to find the most probable model given the data and this led the adoption of Bayesian information criterion.

4.2.3 Consistent Akaike Information Criterion

Consistent Akaike Information Criterion (CAIC) provides an extension to AIC without violating its main principle. In his work Bozdogan, (1987) attempted to improve on the short comings of AIC in an attempt to overcome the tendency of the AIC to overestimate the complexity of the underlying model; and he again observed that the criterion does not directly depend on sample size and as a result lacks certain properties of asymptotic consistency. In formulating CAIC, a correction factor based on the sample size is employed to compensate for the overestimating nature of AIC. CAIC, which reflects sample size and has properties of asymptotic consistency.

$$\mathrm{CAIC} = -2\mathrm{LogLik} + \mathrm{r}\ (\mathrm{Log\ n}) + 1$$

where LogLik refers to the likelihood under the fitted model,

r is the number of parameters in the model and

n is the logarithm of sample size.

4.2.4 Hanna-Qunnie Information Criterion (HQIC)

The Hannan-Quinn information criterion (HQIC) is also a measure of the goodness of fit of a statistical model, and is often used as a criterion for model selection among a finite set of models. It is not based on log-likelihood function, and but related to Akaike's information criterion. Similar to AIC, the HQIC introduces a penalty term for the number of parameters in the model, but the penalty is larger than one in the AIC.HQIC, like BIC, but unlike AIC, is not asymptotically efficient. Most times it is used as an alternative to Akaike information criterion (AIC) and Bayesian information criterion (BIC).

In general, the BIC is defined as: HQIC

$= -2l_{max} + 2k\ln(\ln(n))$

where l_{max} is the log-likehood,

k is the number of parameters, and

n is the number of observations.

4.3 Analysis and Presentation of Results (Real Data)

For the analysis of and presentation of results, monthly data on Nigeria's Gross Domestic Product and external reserve from 1981 to 2015 extracted from the Central Bank of Nigeria statistical bulletin of 2017 were used. The performance of the proposed model was compared with distributed lag model with normal error term using the model criteria AIC, BIC, CAIC, and HQIC. The lower the value of the performance criteria the better the model. For the comparison of forecasting performance, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used. The lower the value of the performance criteria the better the model.

4.3.1 Validation of the Model with Real Data Set

Now we, examined the applicability of the proposed robust DLM model using a real data set. Data sets on GDP and External Reserves were extracted from CBN Statistical Bulletin of 2017 and covers from 1981 to 2015. Exploratory data analysis was performed on the two sets of data in other to determine the nature of the data and thereafter the proposed model was applied to the data.

Table 4.1: Descriptive analysis on GDP Data

Min	1st Quarter	Median	Mean	3rd Quarter	Max	Skewness	Kurtosis
94.33	427.50	4189.00	17830.00	19610.00	94140.00	1.688211	4.405487

Source: Output from the R- programing package

From the descriptive analysis of GDP data as shown in Table 4.1, the data is positively skewed with a value of 1.688211. The skewedness of the data is further confirmed with the value Median (4189.00) being less than the value of the mean (17,830.00). The minimum value and the maximum value of the data are 94.33 and 94140.00 respectively.

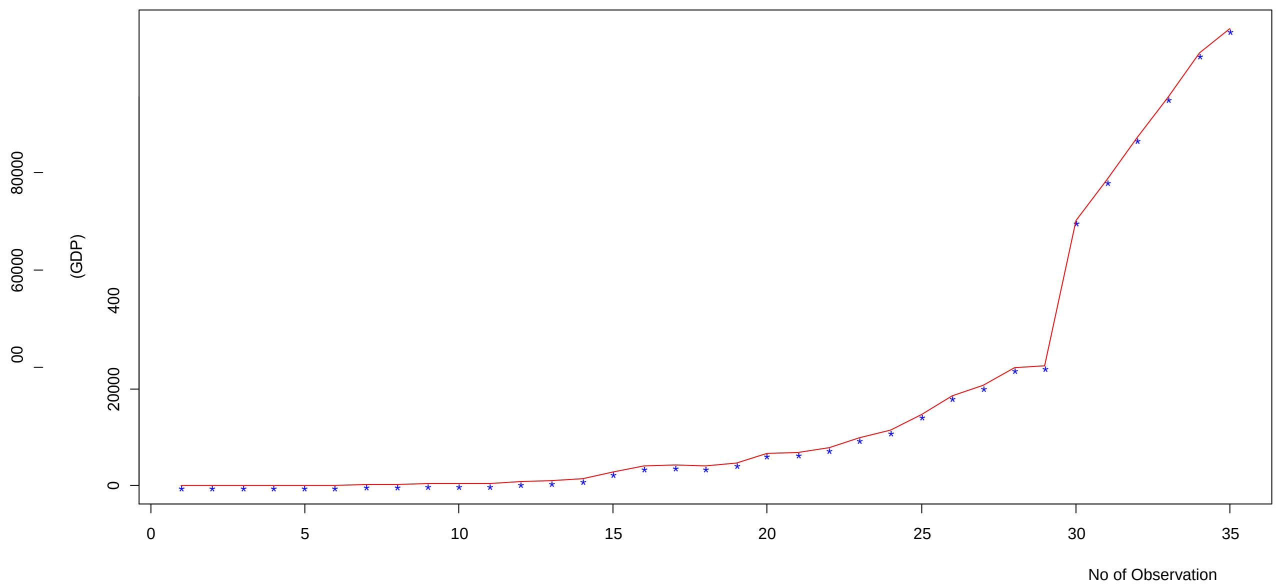

Fig.4.1 Time Plot of the GDP Data

From the time plot of gross domestic product as shown in fig.4.1 above, there was a constant increase in value of gross domestic product from 1981 to 1993. How there was sharp increase from 1996 with a value of 4030.32 compared to a value of 2907.36 in 1995. This represents a 38.63% increase in value. Thereafter, there was a steady increase in value with a peak in 2015 with a value of 4679.21.

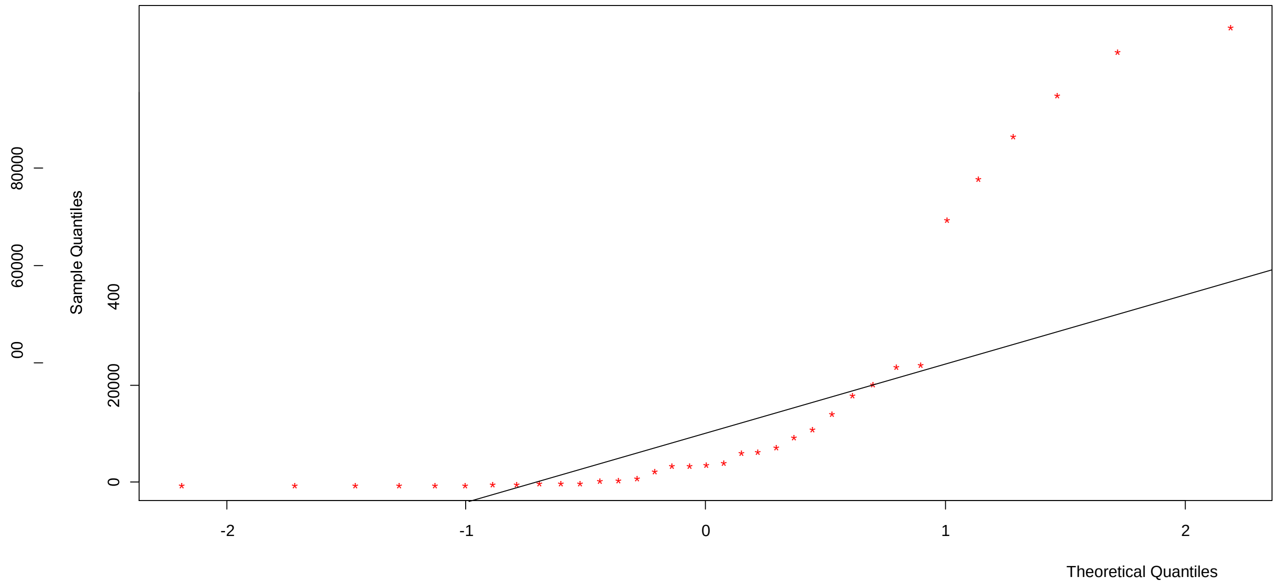

Fig 4.2 GDP Normal Q-Q Plot

The Q-Q plot, or quantile-quantile plot, is a graphical tool to help us assess if a set of data plausibly came from some theoretical distribution such as a Normal or exponential. If the data is normally distributed, the points in the QQ-normal plot lie on a straight diagonal line Now, running a statistical analysis on the dependent variable, GPD, the Normal Q-Q plot for GDP as shown in figure 4.2 indicates that the data is not symmetrical, that is the dependent variable is not normally distributed.

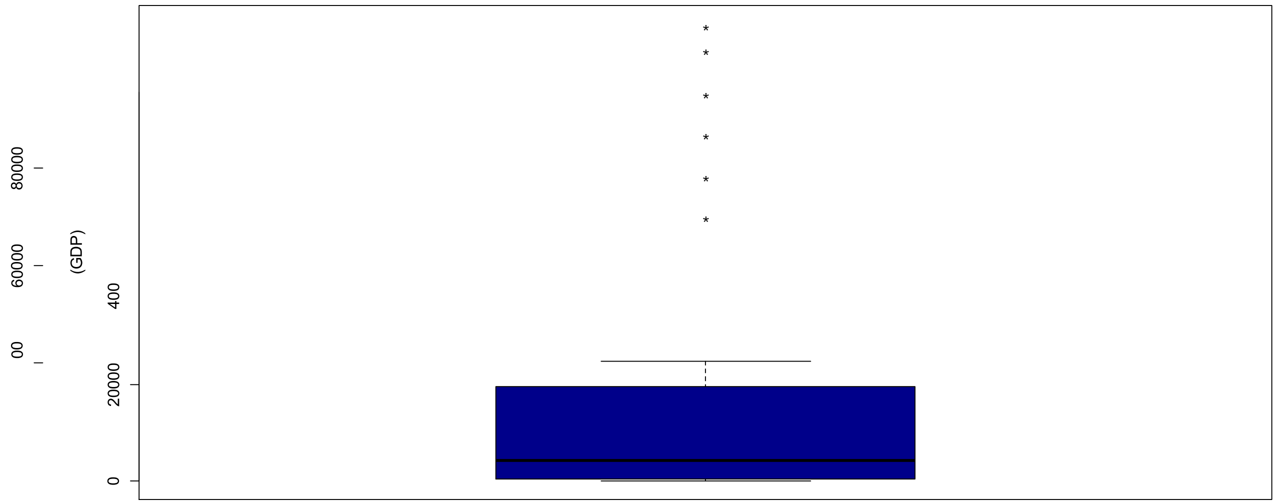

Fig.4.3 Box Plot on GDP

The box plot is a usefull graphical display for describing the behavior of the data in middle as well as the ends of the distributions. It helps in examining the overall shape of the graphed data for important features such as departuresfrom assumptions and symmetry. When reviewing a boxplot, an outlier is defined as a data point that is located outside the fences ("whiskers") of the boxplot.

From the Box plot in fig. 4.3 it shows that gross dosmestic product data contains outliers, because of some data points that are beyond the outer fence the box which makes the data to be skewed.

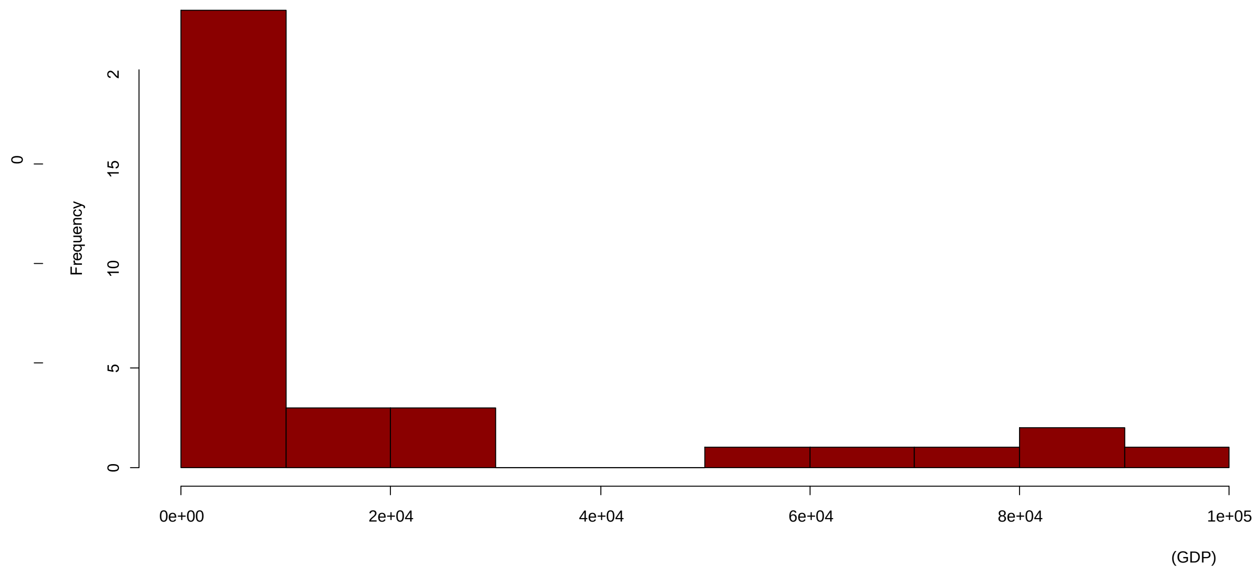

Fig. 4.4 Histogram of GDP

A histogram is an accurate representation of the distribution of numerical data which is an estimate of the probability distribution of continuos variable. It is aplot that lets us discover and show the underlying frequency distribution (shape) of a set of continuous data. From the plot of Histogram of GDP as shown in figure 4.4, indiates that the tail of the histogram tilts to the right confirming that the data is positively skwed.

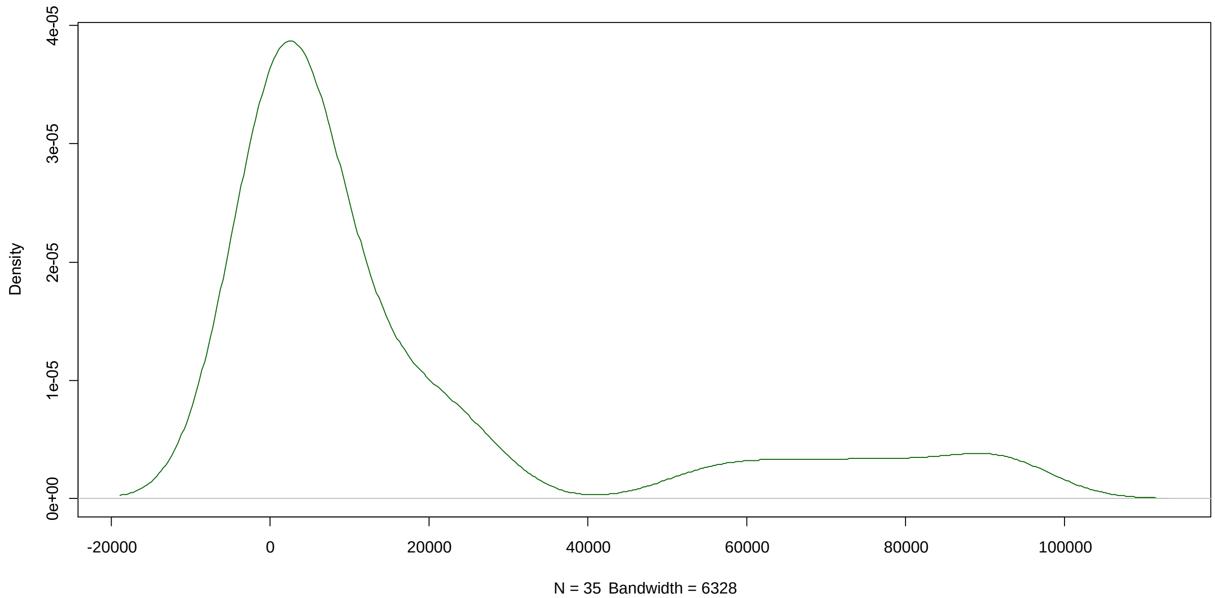

Fig. 4.5 Density plot of GDP

A density plot visualises the distribution of data over a continuous interval or time period. This chart is a variation of a Histogram that uses kernel smoothing to plot values, allowing for smoother distributions by smoothing out the noise. It is a representation of the distribution of a numeric variable. It uses a kernel density estimate to show the probability density function of the variable. It is a smoothed version of the histogram and is used in the same concept. From the plot of density of GPD in figure 4.5, it confirmed that the data is positively skewed.

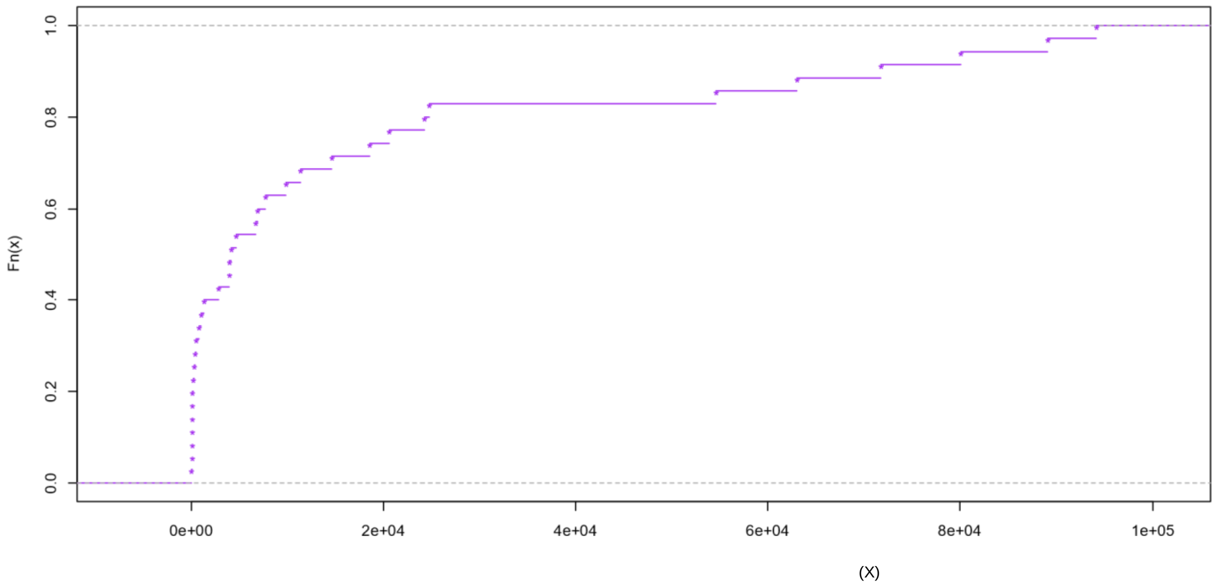

Fig. 4.6 Empirical Cummulative Density function for GDP

An Empirical Cumulative Distribution Function (ECDF) is a non-parametric estimator of the underlying CDF of a random variable. It assigns a probability of to each datum, orders the data from smallest to largest in value, and calculates the sum of the assigned probabilities up to and including each datum. The ECDF calculates the cumulative probability for a given x-value. An ECDF is an estimator of the Cumulative Distribution Function. The ECDF essentially allows you to plot a feature of your data in order from least to greatest and see the whole feature as if is distributed across the data set. An ECDF is an estimator of the Cumulative Distribution Function. The ECDF essentially allows you to plot a feature of your data in order from least to greatest and see the whole feature as if is distributed across the data set as shown in figure 4.6.

Table 4.2: Exploratory Data analysis on External Reserve

Min	1st Quarter	Median	Mean	3rd Quarter	Max	Skewness	Kurtosis
456.6	3510.0	7591.0	15670.0	31190.0	58470.0	1.007664	2.537283

From the descriptive analysis of external reserve data as shown in Table 4.2, the data is also positively skewed with a value of 1.007664. The skewedness of the data is further confirmed with the value of the mean (15,670.00) been greater than the median (7591).

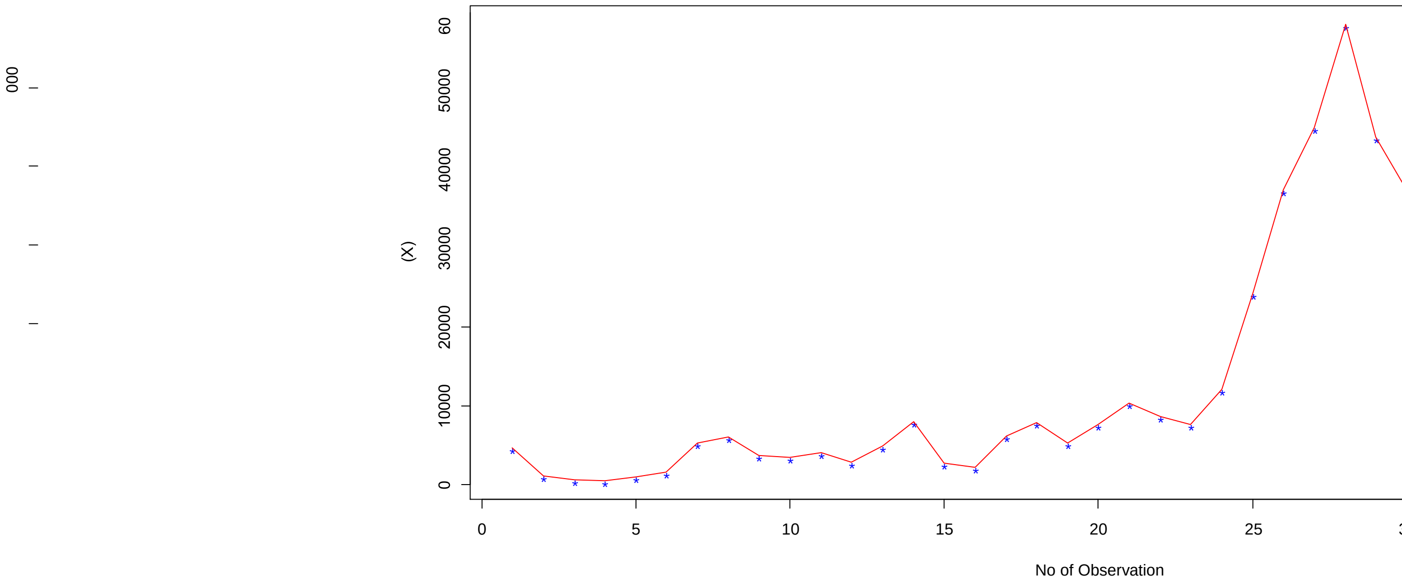

Fig.4.7 Time Plot of External Reserve Data

From the time plot of external reserve data as shown in fig.4.7 above, there was a fluctuating variation in value of gross domestic product from 1981 to 1993. However, there was sharp increase from 1996 with a value of 4030.32 compared to a value of 2907.36 in 1995. This represents a 38.63% increase in value. Thereafter, there was a steady increase in value with a peak in 2015 with a value of 4679.21.

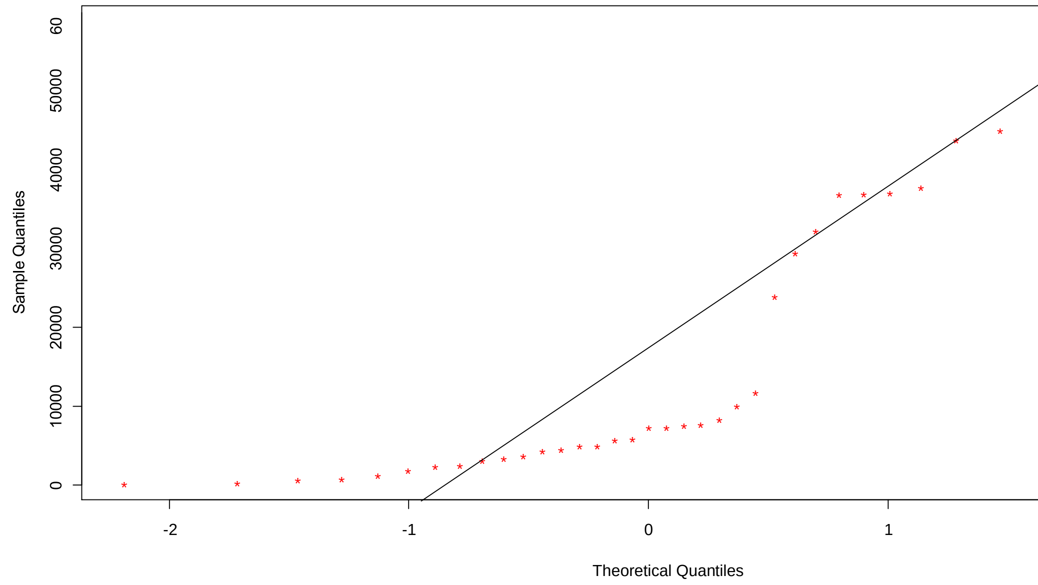

Fig 4.8 Normal Q-Q Plot on External Reserve Data

The Normal Q-Q plot or quantile-quantile plot on external reserve data indicates that the data is not normally distributed because the points does not in the QQ-normal plot lie on a straight diagonal line as shown in figure 4.8 implying that the data is not symmetrical, that is the independent variable is not normally distributed.

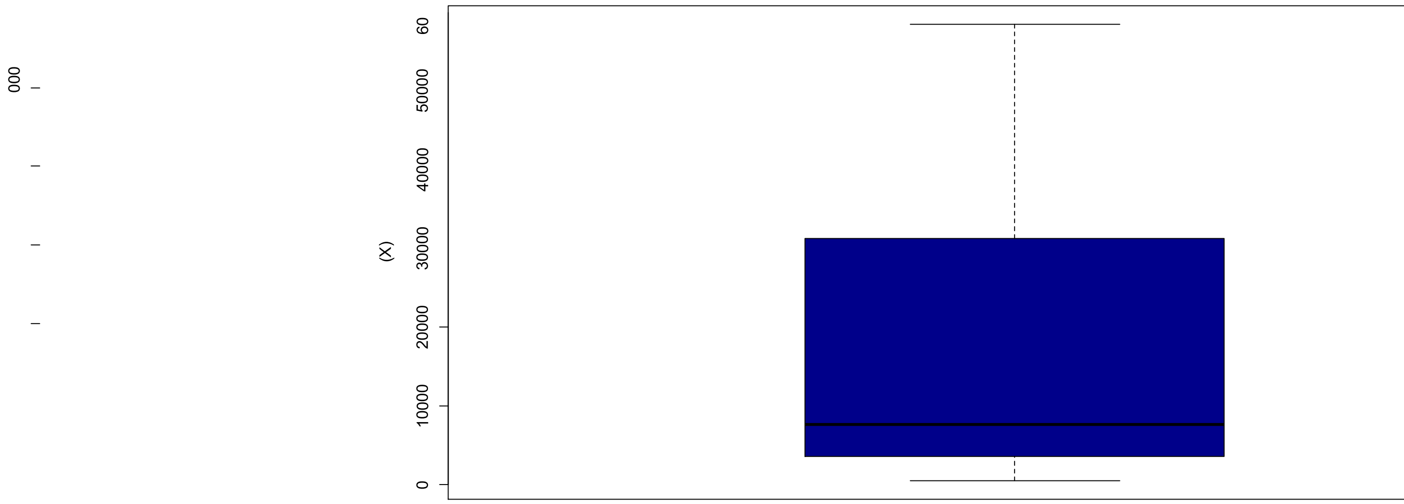

Fig. 4.9 Box Plot on External Reserve

The box plot is a usefull graphical display for describing the behavior of the data in middle as well as the ends of the distributions. It helps in examining the overall shape of the graphed data for important features such as departuresfrom assumptions and symmetry. When reviewing a boxplot, an outlier is defined as a data point that is located outside the fences (“whiskers”) of the boxplot.

From the Box plot in fig. 4.9 it shows that the data on external reserve contains outliers, since some data points that are beyond the outer fence the box which makes the data to be skewed.

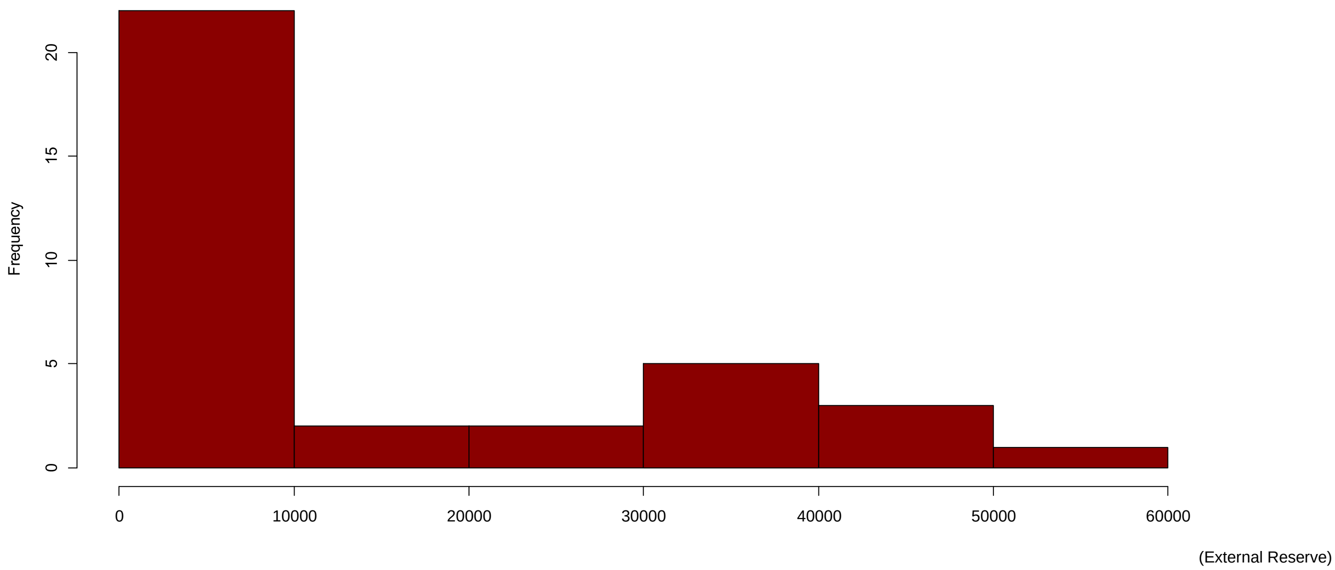

Fig. 4.10. Histogram of External Reserve Data

In order to confirm the nature of data on external reserve the Histogram was plotted as shown in figure 4. 10. Since the tail of the graph tilts to the right, it confirms that the distribution of the external reserve which is the explanatory variable is positively skewed.

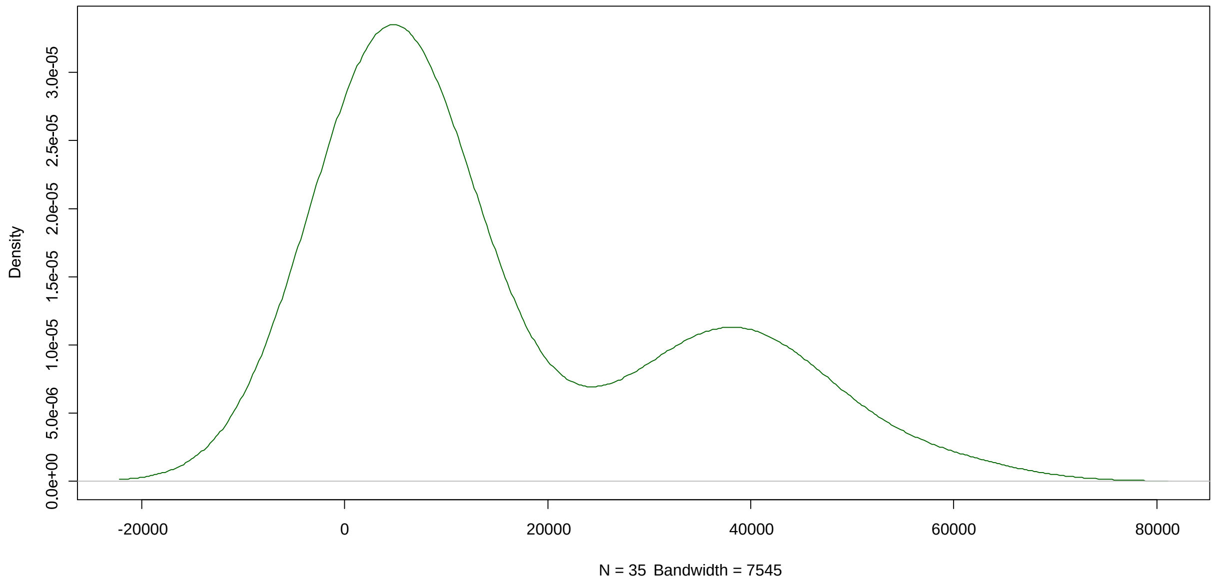

Fig.4. 11 Density plot of External Reserve

A Density Plot visualises the distribution of data over a continuous interval or time period. This chart is a variation of a Histogram that uses kernel smoothing to plot values, allowing for smoother distributions by smoothing out the noise. It is a representation of the distribution of a numeric variable. It uses a kernel density estimate to show the probability density function of the variable. It is a smoothed version of the histogram and is used in the same concept. From the density plot of external reserve in figure 4.11, it confirmed that the data is positively skewed.

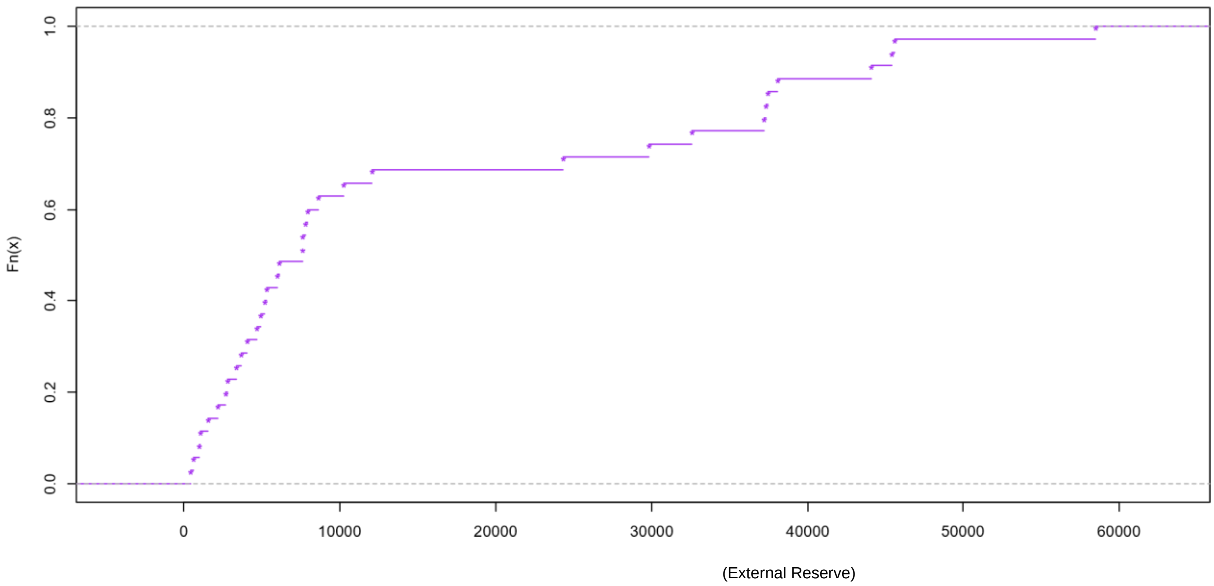

Fig. 4.12 Empirical Cummulative Density function for External Reserve

An Empirical Cumulative Distribution Function (ECDF) is a non-parametric estimator of the underlying CDF of a random variable. It assigns a probability of to each datum, orders the data from smallest to largest in value, and calculates the sum of the assigned probabilities up to and including each datum. The ECDF calculates the cumulative probability for a given x-value. An ECDF is an estimator of the Cumulative Distribution Function. The ECDF essentially allows you to plot a feature of your data in order from least to greatest and see the whole feature as if is distributed across the data set. An ECDF is an estimator of the Cumulative Distribution Function. The ECDF essentially allows you to plot a feature of your data in order from least to greatest and see the whole feature as if is distributed across the data set as shown in figure 4.12.

Table 4.3: Shapiro-Wilk Normality Test on GDP Data

Test	**Shapiro-Wilk Normality Test**
No of observations	35
Test statistic	0.666
P-value	1.15e-07

Source: Output from R-programing package.

Apart from graphical way to determine the level of normality, Shapiro-Wilk is a test of normality in frequentist statistics. The null hypothesis for this test is that the data are normally distributed. If the P-value is greater than 0.05, then the null hypothesis is not rejected. If the test is significant, the distribution is non-normal. From the result on Table 4.3, the P-value is less than 0.05 which indicates that data on gross domestic product is not normally distributed.

Table 4.4 Shapiro-Wilk Normality Test on External Reserve Data

Test	**Shapiro-Wilk Normality Test**
No of observations	35
Test statistic	0.749
P-value	1.28e-04

Source: Output from R-programing package.

From table 4.4 above, the Shapiro-Wilk normality test on the explanatory variable shows a departure from normality for external reserve data since the P-value is less than 0.05.

4.3.2 Results of Analysis from Secondary Data

The result of the proposed model validated with monthly data of Nigeria's Gross Domestic product and external reserve from 1981 to 2015 extracted from the Central Bank of Nigeria statistical bulletin are summarised below:

Table 4.5: Summary Table of Model Evaluation of Secondary Data

Error Innovation	AIC	BIC	CAIC	HQIC
Normal	1695.191	1706.439	1691.384	1698.628
EGND	1590.08	1598.541	1586.274	1593.517

Source: Output from R- programing package

From Table 4.5 above, on model evaluation, the Exponentiated Generalised Normal Distribution perform better than Normal distribution based on the lower values of the criteria. That is, the lower the criteria values the more efficient is the model.

Table 4.6: Forecast Performance

Error Innovations	RMSE	MAE
Normal	4325.37	30839.37
Generalised Exponentiated Normal	1730.508	18348.71

Source: Output from R- programing package

RMSE - Root Mean Square Error

MAE - Mean Absolute Error

The root mean square error and mean absolute are frequently used measure of the differences between values (sample or population values) for the purpose of comparing effectiveness of model performance between two or more models.

From table 4.6, forecast performance indicated that Exponentiated Generalised Normal Distribution perform better than Normal distribution because of its lower root mean square error and mean absolute error values of 1730.50,18348.71 and 4325.37, 30839.37, respectively.

4.4 Presentation of Results (Simulated Data)

For the analysis and presentation of results on simulated data, different sets of simulated data were considered. The first case is with normal data with normal error term and the second scenario is a skewed data with non-normal error term. For each case a varying sample sizes of 20,50, 200, 500, 1000, 5000 and 10,000 of simulated were used. And in order to ensure the stability of the estimates, each simulated data were replicated 10,000 times in other to examine the consistency of the estimated parameters of the models. The performance of the proposed model was compared with distributed lag model with normal error term using AIC, BIC, CAIC, and HQIC as performance comparison criteria. The lower the value of the performance criteria the better the model.

Table 4.7: Model Evaluation Result of Simulated Data for Normal Error Innovation

Error Innovation	**N**	**AIC**	**BIC**	**CAIC**	**HQIC**
Normal EGND	20	67.177 -116.660	70.955 -113.828	64.449 -119.398	67.656 -116.183
Normal EGND	50	151.581 -282.197	159.149 -276.521	148.071 -285.707	153.735 -280.043
Normal EGND	200	568.22 -1533.303	581.393 -1523.423	564.340 -1537.182	572.219 -1529.304
Normal EGND	500	1419.893 -3007.006	1436.743 -2994.368	1415.941 -3010.958	1424.852 -3002.046
Normal EGND	1000	2876.864 -5606.922	2896.491 -5592.201	2872.888 -5610.898	2882.459 -5601.327
Normal EGND	5000	14157.15 -26960.82	14183.21 -26941.27	14153.15 -26964.82	14164 -26953.97
Normal EGND	10000	28220.94 -52853.44	28249.78 -52831.81	28216.94 -52857.44	28228.26 -52846.12

Source: Output from R-programing package

From Table 4.7 above it showed that the developed model Exponentiated generalised normal distribution can also modelled data when the error term is normally distributed. As the sample size increases the lower the values of the performance criteria of developed model compared to the normally distributed model across the four (AIC, BIC, CAIC, and HQIC) performance criteria.

Table 4.8: Model Evaluation Result of Simulated data for Non Normal Error Innovation

Error Innovation	N	AIC	BIC	CAIC	HQIC
Normal EGND	20	101.764 -20.75859	105.5417 -17.92527	99.02712 -23.49543	102.2435 -20.27908
Normal EGND	50	231.1168 -81.11681	238.6841 -75.44135	227.6066 -84.62701	233.27 -78.96355
Normal EGND	100	454.0899 -158.7658	464.4704 -150.9804	450.3323 -162.5233	457.2399 -155.6158
Normal EGND	200	884.9164 -575.6247	898.0896 -565.7448	881.037 -579.5041	888.915 -571.6261
Normal EGND	500	2173.888 -848.3838	2190.738 -835.746	2169.936 -852.3357	2178.847 -843.4243
Normal EGND	1000	4277.085 -1421.464	4296.712 -1406.743	4273.109 -1425.44	4282.68 -1415.869
Normal EGND	5000	21086.72 -7907.839	21112.79 -7888.288	21082.72 -7911.834	21093.57 -7900.986
Normal EGND	10000	42187.53 -16199.51	42216.37 -16177.87	42183.53 -16203.5	42194.85 -16192.18

Source: Output from R-programing package

From the table 4.1, it summarises the simulation result with varying sample sizes ranging from 20 to 10,000 when the error term is not normally distributed. The results showed that the Exponentiated generalised normal distribution outperformed normal distribution at different sample sizes using the AIC, BIC, CAIC and HQIC as model selection criteria.

Table 4.9: Replication on Simulated Data with Normal Error Innovation

Model	N	Estimate	Rep (10000)	ASBIAS
Normal EGND	20	554.333 0.3667	1017 0.477	462.666 0.111
Normal EGND	50	4673.667 0.363	9761 0.467	5087.333 0.103
Normal EGND	200	159.698 0.365	147.562 0.476	12.136 0.110
Normal EGND	500	15465.17 0.367	471.5 0.474	15916.67 0.107
Normal EGND	1000	1992.333 0.368	1519 0.474	473.333 0.106
Normal EGND	5000	4167 0.369	5344 0.474	1177 0.104
Normal EGND	10000	11770.33 0.369	10140 0.474	1630.333 0.104

Source: Output from R-programing package

Result of the average parameters calculated from the simulation result is shown in Table 4.9 above for each model and across each as ample size as well as each level of replications. From the 1000 replicated simulated for different sample sizes considered and the mean of the replicates of the estimates computed in which the absolute bias was determined, the exponentiated generalised normal distribution had smaller bias values for the two different scenarios considered, which implies that the exponentiated generalised normal distribution is better than the normal distribution.

Table 4.10: Replication on Simulated with Non-Normal Error Innovation

Model	n	Estimate	Rep (10000)	ASBIAS
Normal EGND	20	0.318 0.375	0.114 0.488	0.203 0.112
Normal EGND	50	1474.667 0.376	1174 0.453	300.666 0.111
Normal EGND	200	38426.67 0.370	59380 0.482	20953.33 0.111
Normal EGND	500	6815.333 0.377	9948 0.488	5132.667 0.111
Normal EGND	1000	14463.33 0.379	17210 0.488	2846.667 0.109
Normal EGND	5000	19360 0.378	13350 0.488	6010 0.109
Normal EGND	10000	45472.67 0.378	7065 0.487	38407.67 0.109

Source: Output from R-programing package

From table 4.10, it depicts the simulated data that were replicated 1000 times for the different sample sizes considered and the mean of the replicates of the estimates computed in which the absolute bias was calculated and compared between the two models. The Exponentiated generalised normal distribution has smaller bias values when the error term is not normally distributed compared to normal distribution for all the sample sizes considered.

4.5 Discussion of Results

In this section, outcome of the analysis of results will be discussed. The first aspect will be on the exploratory data analysis of the secondary data and secondly is the modelling of the secondary data with the developed model and finally modelling of the simulated data with the developed model.

From the descriptive analysis for gross domestic product data as shown in Table 4.1, it indicated that data is positively skewed with a value of 1.688. The skewedness of the data is further confirmed with the median value of 4189.00 been less than the value of the mean 17,830.00. Also from the exploratory data analysis on external reserve data on Table 4.5 showed that the data is not normally distributed with the value of coefficient of skewedness equal 1.007664. The skewedness of the data was further confirmed with the value of the mean 15,670.00 been greater than the median 7591.

Also on the real life data for both for gross domestic product and external reserves, the ShapiroWilk test statistic as shown in Tables 4.3 and 4.4 respectively confirmed the non-normality of both data with P-value less than 0.05 thereby rejecting the null hypothesis of normality. Furthermore on exploratory data analysis, Figs 4.2 and 4.9 depicting Normal Q-Q plots for both for gross domestic product and external reserve respectively showed that both data are not normally distributed.

The skewedness of both and external reserve data were confirmed with the plotting of Histograms of the two data as indicated in figs 4.4 and 4.11respectively showed that both data were positively skewed. The density plots of both data were depicted by figures 4.5 and 4.12 for gross domestic product and external reserve respectively. The tails of the density curves for both graphs tilt to the right thereby confirming that both data are positively skewed.

The Box plots constructed for gross domestic product and external reserve data as shown in figures 4.3 and 4.10 respectively clearly indicate the presence of outliers which may likely be the cause of the departure of both data from normal distribution.

On model evaluation for the developed model of exponentiated generalised normal distribution and normal distribution using the real life data, the result showed that exponentiated generalised normal distribution performed better than normal distribution as indicated by performance criteria AIC, BIC, CAIC and HQIC with values of 1695.191, 1706.439, 1691.384, and 1698.628 for normal distribution as against the corresponding lower values of 1590.08, 1598.541, 1586.274, and 1593.517 respectively as shown in Table 4.5.

Comparing the forecast performance evaluation of each model, as shown in Table 4.6, the error measured for each model, indicated that exponentiated generalised normal distribution is more efficient than normal distribution for forecasting because it has lower root mean square error and mean absolute error values of 1730.508, 18348.71 and 4325.37, 30839.37 compared respectively.

On simulation, two different sets of simulated data were considered. The first case is a situation with normal data with normal error term and the second scenario is a skewed data with non-normal error term. In each case, a varying sample sizes of 20, 50, 200, 500, 1000, 5000 and 10,000 of simulated data were used in order to ensure the stability of the estimates, each simulated data were replicated 10,000 times in other to examine the consistency of the estimated parameters of the models.

The result from the simulated data of sizes 20, 50, 200, 500, 1000, 5000 and 10,000 when the error innovation is assumed to be normal as shown in Table 4.7 had AIC values of 67.18, 151.58, 568.22, 1419.89, 2876. 86, 14156.15, 28220.94, respectively for DLM with normal error term. For DLM with EGNET, the AIC values were -40.01, -116.66, -282.19, -655.10, -1533.01, -3007.01, 5606.92, -26960.82, and -5283.44, respectively.

Considering other performance criteria which include BIC, CAIC and HQIC as summarised in Table 4.7 for simulated data, the exponentiated generalised normal distribution perform better than the Normal distribution based on the lower values of the performance criteria as the sample size increases. That is, the lower the criteria value the more efficient is the model.

For the second case of skewed simulated data with non-normal error term at various sample sizes of 20, 50, 200, 500, 1000, 5000 and 10,000 as shown in Table 4.8, the exponentiated generalised normal distribution is considerably and consistently more efficient than the normal distribution as a result of having lower criteria values with all performance criteria under consideration i.e. AIC, BIC, CAIC and HQIC various sample sizes.

Finally on simulation, Tables 4.9 and 4.10 summarised the results of the average parameters calculated from the simulation result for each model across each sample size as well as each level of replications on simulated data both for normal error innovation and non-normal error innovation respectively. From the 1000 replicated simulated for different sample sizes considered and the mean of the replicates of the estimates computed in which the absolute bias was determined, the exponentiated generalised normal distribution had smaller bias values for the two different scenarios considered. From Table 4.10, the absolute bias for normal distribution are 462.6667, 5087.333, 12.13667, 15916.67, 473.333, 1177, 1630.333 for sample sizes of 20, 50, 200, 500, 1000, 5000 and 10,000 respectively. The corresponding absolute bias for exponentiated generalised normal distribution respectively are 0.11106, 0.103515, 0.1108082, 0.107225, 0.1061475 0.10491, 0.1044025 and 0.1044025. From these results, the Exponentiated generalised normal distribution has smaller bias values when the error term is normally distributed.

For the case of replication on simulated data with non-normal error innovation, absolute bias for normal distribution are 2039833, 300.6667, 20953.33, 5132.667, 2846.667, 6010 and 38407.67 while that of exponentiated generalised normal distribution are 0.1123725, 0.11148, 0.1118175, 0.11141, 0.1092025, 0.109385 and 0.1094625 for the various sample sizes considered as depicted in Table 4.10. This implies that the estimates of the parameters of the developed model, exponentiated generalised normal distribution are more consistent compared to normal distribution in modelling distributed lag model with data that exhibits high degree of asymmetry.

CHAPTER FIVE

SUMMARY AND CONCLUSION

5.1 Summary

As a result of dynamism of distributed lag model and being a major workhorse in dynamic singleequation regression, there is, in most cases violation of normality of the error term which is one of the critical assumptions of distributed lag model and when there is a violation or missspecification of the error term there will be unreliable estimate of the parameters and forecasted values from the model will also be unreliable. Violations of other assumptions had been considered in previous studies like multicollinearity, autocorrelation and non-linearity, but not the exponentiated generalised normal error term of the general form of distributed lag model (Goldstein 1995, Maos and Hox 2013). As a result of this, a robust distributed lag model was developed that enhanced inference when the assumption of normality of error term is violated.

For the methodology, a conceptual framework was developed through which parameters of the distributed lag model was obtained in the presence of normal error assumption violation. The existing two parameters power exponential distribution was extended with the introduction of one extra shape parameter giving rise to Exponentiated generalised normal distribution which has a better shape and broader tail. The distributed lag models both for the normal and non-normal error innovations were specified and parameters of the distributed lag model distributed lag models with both normal error and non-normal innovation were then estimated. Exponentiated generalised normal distribution was used to model the general form of distributed lag models and method of maximum likelihood estimation was used in estimating the parameters of the model. The Fisher's information matrix and variance of each of the parameter were obtained. The appropriate inference on parameters of the model which included the construction of confidence intervals and test of hypothesis were derived.

Using simulated data of varying sample sizes, it showed that exponentiated generalised normal distribution apart from its flexibility has better representation of distributed lag model with nonnormal error term.

It was observed that if a set of data is skewed or with non-normal error distribution for whatever the sample size considered, the conventional assumption of normality is invalid but instead, Exponentiated generalised normal error innovation is more appropriate and efficient is estimating the parameters of the general form of distributed lag model.

From the summary of the results for both simulated data of various sample sizes and secondary data sets, we can confidently conclude that Exponentiated generalised normal distribution can effectively model distributed lag model of general form when the error term is not normally distributed.

On model evaluation for the developed model of exponentiated generalised normal distribution and normal distribution using the real life data, the result also showed that exponentiated generalised normal distribution performed better than normal distribution as indicated by various performance criteria used.

5.2 Conclusion

Distributed lag model which is a major workhorse in dynamic single-equation regression and requires stringent assumptions for its validity. For distributed lag models, one of its critical assumptions is the normality of the error term which is often violated in practice and often leads to spurious inference and poor forecast performance. Violations of other assumptions had been considered in previous studies but not the exponentiated generalised normal error term of the distributed lag model. It was as a result of this identified gap that this study was designed to develop a robust distributed lag model that could enhance inference when the assumption of normality of error term is violated.

Conclusively, judging from the smaller values of selection criteria and forecast performance of error measurement, the distributed lag model with exponentiated generalised normal error innovation is more efficient than distributed lag models with normal error term. This implies that the exponentiated generalised with normal error innovation is remarkably more efficient and robust than the normal distribution in modelling and estimating parameters of the distributed lag models. Also, forecast performance indicated that exponentiated generalised normal distribution is better than normal distribution because of its lower root mean square error and mean absolute error.

The distributed lag model with exponentiated generalised normal error term showed improved forecasting and inference even when the residual term were not normally distributed. It is therefore recommended for normally distributed and skewed data sets.

5.3 Contributions to Knowledge

With the realisation that distributed lag models with normal error innovation are not efficient in modelling dynamic relationship between two or more variables, a distributed lag model with nonnormal error innovation had been developed to provide solution to the estimation problems under non-normality of the error distribution of general form of distributed lag models.

The developed model has shown to provide a better fit and it can effectively model distributed lag model of general form when the data exhibits skewness, the error term is not normally distributed or the data contain outliers.

5.4 Area for Further Studies

Further research could involve comparing the performance of the developed model to other family of skewed distributions such as Generalised Power Exponential Error Innovation, Length Biased and Generalised Gamma normal for distributed lag models using both real and simulated data sets.

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APPENDIX A

R CODES FOR DATA ANALYSIS AND OUTPUT

```
set.seed(5840) # this makes the example exactly reproducible
       N      <- 500
        x      <- rnorm(N)
   beta  <-     0.4     errors     <-     rgamma(N,
  shape=1.5, scale=1)
   errors <- rgamma(N, shape=1.5, scale=2)
  # errors <1*errors     # this makes them left skewed y
            <- 1 + x*beta + errors
library(maxLik) library(stats)
library(sandwich)
  shapiro.test(y)
y1=y[-1] x1=x[-1]
lagx1=x[-500]
lagy1=y[-500]
n=500

loglik2<-function(p)                          -n*log(p[1])+(p[1]-1)*sum(log(dnorm(y1,mean(y1),sd(y1))))-
0.5*n*log(2*pi*var(y1))-0.5*sum((y1-p[2]*x1-p[3]*lagx1)^2/sd(y1))   b
 <- maxLik(loglik2, start=c(1.5,1.5,1.5))
summary(b) AIC(b)
norm=lm(y1~x1+lagx1)
summary(norm)
AIC(norm)
set.seed(5840) # this makes the example exactly reproducible
       N      <- 1000
        x      <- rnorm(N)
   beta  <-     0.4     errors     <-     rgamma(N,
  shape=1.5, scale=1)
```

```
  errors <- rgamma(N, shape=1.5, scale=2)
 # errors <1*errors     # this makes them left skewed y
          <- 1 + x*beta + errors
 shapiro.test(y)
y1=y[-1] x1=x[-1]
lagx1=x[-1000]
lagy1=y[-1000]
n=1000 loglik2<-function(p)  -n*log(p[1])+(p[1]-1)*sum(log(dnorm(y1,mean(y1),sd(y1))))-
0.5*n*log(2*pi*var(y1))-0.5*sum((y1-p[2]*x1-p[3]*lagx1)^2/sd(y1))
b <- maxLik(loglik2, start=c(1.5,1.5,1))
summary(b) AIC(b)
norm=lm(y1~x1+lagx1)
 summary(norm) AIC(norm)
library(maxLik) library(stats)
library(sandwich)
mydata=read.csv('datanew.csv', header=T)
attach(mydata) shapiro.test(Gdp)#...test of
normality y1=Gdp x=ExtRes
y2=y1[-1]#... lagging y1 once xnew=x[-1]#... lagging y once lagx=x[-
length(x)] #.... when laging from t to i lagy=y1[-length(y1)] #.... when laging
from t to j hist(y1,main='Histogram plot of the GDP data', prob = TRUE,
xlab='GDP') lines(density(y1, adjust=1.5), lty="dotted", col="red", lwd=2)

hist(x,main='Histogram of the External Reserve', prob = TRUE) lines(density(x,
adjust=1.5), lty="dotted", col="red", lwd=2)

# yt = a + bxt-i + byt-j Model to be fitted

norm=lm(y2~lagx+lagy)

summary(norm) AIC(norm)
```

```
BIC(norm)

AICc = AIC(norm) + ((2*3)*(3+1)/length(y2)-3-1)
AICc

HQIC = 2*3*log(log(length(y2)))- ((2*3)-AIC(norm))
HQIC
#...........Exponentiated Generalised Normal

loglik2<-function(p)                                              -length(y2)*log(p[1])+(p[1]-
1)*sum(log(p[2])*(dnorm(y2,mean(y2),sd(y2))))-0.5*length(y2)*log(2*pi*var(y2))-
(0.5/var(y2))*sum((y2-p[3]*lagx-p[4]*lagy)^2) b
<- maxLik(loglik2, start=c(1.5,1.5,1.5,1.5))
summary(b)

AIC(b)

BIC = 3*log(length(y1)) - ((2*3)-AIC(b));BIC
AICc = AIC(b) + ((2*3)*(3+1)/length(y1)-3-1);AICc
HQIC = 2*3*log(log(length(y1)))- ((2*3)-AIC(b));HQIC

#.... Real data ends here

#####################################################################################
#                         SIMULATION BEGINS HERE                    #
#####################################################################################
#

#..........................................................................
#... Normal data & Normal Error
```

```
n=10
set.seed(30) normData1 =
rnorm(n,5, 2) err=
rnorm(n,0,1)
model=lm(normData1~err)
model$coef
y=model$coef[1] + model$coef[2]*normData1

set.seed(34) normData2 = rnorm(n,0, 2) err2=
rnorm(n,0,1) model2=lm(normData2~err2)
model2$coef x=model2$coef[1] +
model2$coef[2]*normData2 ynew=y[-1]#...
lagging y once lagy=y[-length(y)] #.... when laging
from t to i xnew =x[-1]# ...lag once lagx=x[-
length(x)]

norm2=lm(ynew~lagx+lagy)
summary(norm2) AIC(norm2)

BIC(norm2)

AICc = AIC(norm2) + ((2*3)*(3+1)/length(y2)-3-1);AICc

HQIC = 2*3*log(log(length(y2)))- ((2*3)-AIC(norm2));HQIC

#...........Exponentiated Generalised Normal

loglik2<-function(p)                                          -length(ynew)*log(p[1])+(p[1]-
1)*sum(log(p[2])*(dnorm(ynew,mean(ynew),sd(ynew))))-
0.5*length(ynew)*log(2*pi*var(ynew))-(0.5/var(ynew))*sum((ynew-p[3]*xnew-p[4]*lagy)^2) b
<- maxLik(loglik2, start=c(0.5,0.5,0.5,0.2)) summary(b)
```

```
AIC(b)

BIC = 3*log(length(y1)) - ((2*3)-AIC(b));BIC
AICc = AIC(b) + ((2*3)*(3+1)/length(y1)-3-1);AICc
HQIC = 2*3*log(log(length(y1)))- ((2*3)-AIC(b));HQIC
#....................................... ends ....................................
#       -Normal data non normal error term

set.seed(30) normData1 = rnorm(n,5, 2) err= rweibull(n,2,3)
model=lm(normData1~err) model$coef y=model$coef[1] + model$coef[2]*normData1

set.seed(34) normData2 = rnorm(n,0, 2) err2= rweibull(n,2,3)
model2=lm(normData2~err2) model2$coef x=model2$coef[1] +
model2$coef[2]*normData2

ynew=y[-1]#... lagging y once lagy=y[-length(y)] #.... when laging from t to i xnew
=x[-1]# ...lag once lagx=x[-length(x)]

norm2=lm(ynew~lagx+lagy) summary(norm2) AIC(norm2)

BIC(norm2)

AICc = AIC(norm2) + ((2*3)*(3+1)/length(y2)-3-1);AICc HQIC = 2*3*log(log(length(y2)))-
((2*3)-AIC(norm2));HQIC

#...........Exponentiated Generalised Normal

loglik2<-function(p)        -length(ynew)*log(p[1])+(p[1]-
1)*sum(log(p[2])*(dnorm(ynew,mean(ynew),sd(ynew))))-
```

```
0.5*length(ynew)*log(2*pi*var(ynew))-(0.5/var(ynew))*sum((ynew-p[3]*xnew-p[4]*lagy)^2) b
<- maxLik(loglik2, start=c(0.5,0.5,0.5,0.2)) summary(b)

AIC(b)

BIC = 3*log(length(y1)) - ((2*3)-AIC(b));BIC
AICc = AIC(b) + ((2*3)*(3+1)/length(y1)-3-1);AICc
HQIC = 2*3*log(log(length(y1)))- ((2*3)-AIC(b));HQIC

#        -Skewed data with normal error term

set.seed(30) normData1 =
rweibull(n,2,3)
hist(normData1, prob=T)
lines(density(normData1))
err= rnorm(n,0,1)
model=lm(normData1~err)
model$coef
y=model$coef[1] + model$coef[2]*normData1

set.seed(34) normData2 =
rweibull(n,2,3) err2=
rnorm(n,0,1)
model2=lm(normData2~err2)
model2$coef
x=model2$coef[1] +
model2$coef[2]*normData2
ynew=y[-1]#... lagging y once
lagy=y[-length(y)] #.... when
laging from t to i xnew =x[-1]#
...lag once lagx=x[-length(x)]
```

```
norm2=lm(ynew~lagx+lagy)
summary(norm2) AIC(norm2)

BIC(norm2)

AICc = AIC(norm2) + ((2*3)*(3+1)/length(y2)-3-1);AICc

HQIC = 2*3*log(log(length(y2)))- ((2*3)-AIC(norm2));HQIC

#...........Exponentiated Generalised Normal

loglik2<-function(p)                                         -length(ynew)*log(p[1])+(p[1]-
1)*sum(log(p[2])*(dnorm(ynew,mean(ynew),sd(ynew))))-
0.5*length(ynew)*log(2*pi*var(ynew))-(0.5/var(ynew))*sum((ynew-p[3]*xnew-p[4]*lagy)^2) b
<- maxLik(loglik2, start=c(0.5,0.5,0.5,0.2)) summary(b)

AIC(b)

BIC = 3*log(length(y1)) - ((2*3)-AIC(b));BIC
AICc = AIC(b) + ((2*3)*(3+1)/length(y1)-3-1);AICc
HQIC = 2*3*log(log(length(y1)))- ((2*3)-AIC(b));HQIC
#        -Skewed data with non normal error term and then

set.seed(30) normData1 = rweibull(n,1,2) hist(normData1, prob=T)
lines(density(normData1)) err= rweibull(n,2,1) model=lm(normData1~err) model$coef
y=model$coef[1] + model$coef[2]*normData1

set.seed(34) normData2 = rweibull(n,1,2) err2= rweibull(n,2,1)
model2=lm(normData2~err2) model2$coef x=model2$coef[1] +
model2$coef[2]*normData2
```

ynew=y[-1]#... lagging y once lagy=y[-length(y)] #.... when laging from t to i xnew =x[-1]# ...lag once lagx=x[-length(x)]

norm2=lm(ynew~lagx+lagy) summary(norm2) AIC(norm2)

BIC(norm2)

AICc = AIC(norm2) + ((2*3)*(3+1)/length(y2)-3-1);AICc HQIC = 2*3*log(log(length(y2)))-((2*3)-AIC(norm2));HQIC

#...........Exponentiated Generalised Normal
loglik2<-function(p) -length(ynew)*log(p[1])+(p[1]-1)*sum(log(p[2])*(dnorm(ynew,mean(ynew),sd(ynew))))-0.5*length(ynew)*log(2*pi*var(ynew))-(0.5/var(ynew))*sum((ynew-p[3]*xnew-p[4]*lagy)^2) b <- maxLik(loglik2, start=c(0.5,0.5,0.5,0.2)) summary(b)
AIC(b)
BIC = 3*log(length(y1)) - ((2*3)-AIC(b));BIC
AICc = AIC(b) + ((2*3)*(3+1)/length(y1)-3-1);AICc
HQIC = 2*3*log(log(length(y1)))- ((2*3)-AIC(b));HQIC
#In other to archieve all these we, four sets of data will be simulated:
- Normal data with normal error
-Skewed data with non normal error term and then

layout(matrix(c(1,2),1,2)) plot(GDP,col="black",pch="*",xlab="Observation",main="Gross Domestic Product Scatter Plot")

plot(EXT,col="blue",pch="*",xlab="Observation",main="External Reserves Scatter Plot")

plot(GDP,col="black",pch="*",xlab="Observation",main="Gross Domestic Product Plot")

lines(GDP,col="black",pch="*",xlab="Observation",main="Gross Domestic Product Plot")

plot(EXT,col="blue",pch="*",xlab="Observation",main="External Reserves of Crude Oil Plot")

lines(EXT,col="blue",pch="*",xlab="Observation",main="External Reserves of Crude Oil Plot")

layout(matrix(c(1,2,3,4,5,6),3,2))

plot(GDP,pch="*",col="blue",ylab="GDP",xlab="No of Observation",main="Gross Domestic Product Line-Plot") lines(GDP,pch="*",col="black",ylab="GDP",xlab="No of Observation",main="Gross Domestic Product Line-Plot") qqnorm(GDP,pch="*",col="black",main="Gross Domestic Product Normal Q-Q Plot") qqline(GDP,pch="*",col="red",ylab="GDP",main="Gross Domestic Product Normal Q-Q Plot") boxplot(GDP,pch="*",col="blue",ylab="GDP",main="Gross Domestic Product BoxPlot") hist(GDP,pch="*",col="purple",xlab="GDP",main="Gross Domestic Product Histogram Plot") plot((density)(GDP),pch="*",col="darkred",main="Gross Domestic Product Density Plot") plot((ecdf)(GDP),pch="*",col="darkblue",xlab="No of Observation",main="Gross Domestic Product ecdf Plot") plotdist(GDP,col="red",pch="*",histo=TRUE,demp=TRUE)

APPENDIX B

SECONDARY DATA

Data on GDP and External Reserves (1981-2015) extracted from CBN Statistical Bulletin.

Year	GDP (y)	EXT Res.(x)		
1	94.33	4682.900	-	-
2	101.01	1027.025	4682.900	94.33
3	110.06	597.617	1027.025	101.01
4	116.27	456.642	597.617	110.06
5	134.59	981.808	456.642	116.27
6	134.60	1576.842	981.808	134.59
7	193.13	5212.850	1576.842	134.60
8	263.29	6022.233	5212.850	193.13
9	382.26	3662.750	6022.233	263.29
10	472.65	3357.750	3662.750	382.26
11	545.67	4051.675	3357.750	472.65
12	875.34	2782.650	4051.675	545.67
13	1089.68	4902.025	2782.650	875.34
14	1399.70	7944.092	4902.025	1089.68
15	2907.36	2695.417	7944.092	1399.70
16	4032.30	2157.983	2695.417	2907.36
17	4189.25	6124.350	2157.983	4032.30
18	3989.45	7814.733	6124.350	4189.25
19	4679.21	5309.100	7814.733	3989.45

20	6713.57	7590.767	5309.100	4679.21
21	6895.20	10277.492	7590.767	6713.57
22	7795.76	8592.008	10277.492	6895.20
23	9913.52	7641.825	8592.008	7795.76
24	11411.07	12062.758	7641.825	9913.52
25	14610.88	24320.767	12062.758	11411.07
26	18564.59	37456.092	24320.767	14610.88
27	20657.32	45394.317	37456.092	18564.59
28	24296.33	58472.892	45394.317	20657.32
29	24794.24	44702.358	58472.892	24296.33
30	54612.26	37355.708	44702.358	24794.24
31	62980.40	32580.275	37355.708	54612.26
32	71713.94	38092.158	32580.275	62980.40
33	80092.56	45612.942	38092.158	71713.94
34	89043.62	37220.333	45612.942	80092.56
35	94144.96	29805.483	37220.333	89043.62

Source: CBN Statistical Bulletin (2017)

APPENDIX C

SOME SIMULATED DATA FROM NORMAL AND SKEWED DISTRIBUTION

When n = 2000

y ~ N()

sim_error1 ~ exp() sim_error2 ~
exp() sim_error11~exp()
sim_error22~ webull()

	y	sim_error	sim_error2	sim_error11	sim_error22
1	1.512987	0.604068	0.566854	2.076888	0.417738
2	2.120756	0.879343	1.845807	2.622421	0.144985
3	0.750212	0.333652	1.272161	1.532682	0.413706
4	1.300145	0.453618	2.546556	0.501243	0.191339
5	2.662471	1.656026	3.916173	0.380894	0.028748
6	1.446658	0.344632	3.021022	0.961789	7.39E-06
7	1.585655	0.672221	3.836312	5.118516	0.01905
8	3.947998	3.471489	6.963035	2.462923	0.714862
9	1.889366	0.523142	2.311418	0.066501	6.98E-07
10	1.990012	1.520361	2.906432	3.625599	0.083185
11	3.146133	2.031135	5.287071	0.261031	0.225476
12	2.959332	2.029823	0.406316	3.312592	0.044993
13	3.545059	2.229669	1.950468	2.905167	0.000222
14	1.232488	0.611203	5.480472	0.2715	6.70E-05
15	1.999777	1.220064	0.380436	1.06931	0.195526
16	3.691099	3.538011	0.18	2.575013	7.23E-07
17	3.354891	2.57547	0.557412	1.965742	4.70E-05
18	2.918826	1.938867	9.531949	2.496276	0.896718
19	2.985057	2.12563	3.505017	0.942275	0.157791
20	2.978843	1.76168	9.016646	0.779664	5.99E-06
21	3.423709	2.163075	6.017368	3.495215	0.373549
22	1.886828	0.960462	1.946223	0.837268	0.003877
23	2.107501	1.337731	1.759639	0.392131	0.04198
24	0.782929	0.741151	1.892442	0.368256	0.017257
25	6.28327	5.128046	3.228732	0.302538	0.01135
26	3.243299	2.137599	3.363015	2.100777	5.86E-05
27	3.254794	2.015876	5.799821	0.994232	0.136576
28	1.968802	1.135036	4.936419	0.207219	0.273201
29	1.100391	0.553114	1.370249	1.515586	0.011063
30	0.4652	0.148103	1.074981	1.183104	0.046298

31	4.769213	4.105005	1.947414	0.42826	8.22E-21
32	1.027911	0.489801	12.05402	0.530559	0.504321
33	6.917209	5.956044	1.532314	4.764592	9.06E-08
34	4.047987	2.955471	1.658543	3.125913	2.00E-05
35	2.566725	0.935463	1.323629	1.524988	1.418726
36	1.701044	0.902553	0.680098	3.585121	0.016208
37	4.13843	2.788869	2.128266	3.431258	0.001894
38	4.141221	2.394079	4.300223	0.264907	4.00E-06
39	1.034157	0.205196	4.151426	3.81065	0.052466
40	1.652529	0.171172	0.888783	1.740614	0.029905
41	1.571346	0.534793	6.437051	1.224793	0.001064
42	4.225975	3.210305	3.132904	0.491056	0.006159
43	2.416843	1.683043	0.855064	0.305754	0.000156
44	2.607748	1.595513	4.704396	3.274033	0.127993
45	1.366754	0.551487	1.871475	1.198101	0.53957
46	1.193173	0.679245	2.857196	0.050191	0.829439
47	1.528087	0.153765	1.553889	5.983742	0.001268
48	1.339901	0.589542	1.462633	0.226043	0.044059
49	1.461727	0.513062	6.552013	0.564468	0.160184
50	2.885021	2.0025	4.18721	0.435634	0.085366
51	1.153039	0.366623	2.31515	1.380367	0.000119
52	3.71211	2.524396	2.698325	6.286151	0.000638
53	1.829556	1.121001	0.197613	2.063731	2.27548
54	3.102146	1.777835	0.552925	0.89126	0.380019
55	3.307761	2.879213	7.621772	0.000305	1.14E-07
56	1.516249	0.784353	2.084984	3.190629	0.230781
57	1.925873	0.684411	3.335408	4.388285	0.002286
58	1.839039	0.795607	0.891327	1.632988	0.006594
59	2.417678	1.525562	1.440999	0.41476	0.001246
60	2.831468	1.121663	6.123748	1.429622	0.188827
61	3.736296	2.243119	1.531663	0.771941	0.224691

62	1.129864	0.142252	3.145982	1.465162	8.62E-05
63	3.691475	1.715966	4.031926	2.237272	9.94E-07
64	2.269331	0.870327	2.562957	2.888386	0.073176
65	3.288235	2.593017	3.917031	0.28194	0.065948
66	2.492451	1.426891	5.102882	0.178867	0.000207
67	2.264588	1.32212	0.848949	1.069305	0.779934
68	1.681598	0.562903	5.712246	3.301635	0.000471
69	1.964877	0.170164	5.37052	0.168601	0.20941
70	1.904765	0.992844	4.247585	3.57176	0.052657
71	1.214541	0.571161	3.547506	2.082731	6.01E-07
72	1.736948	0.852228	4.751285	2.545648	0.026332
73	5.559466	4.244555	2.154113	0.921593	7.94E-11
74	1.946072	0.924705	1.774492	1.821619	0.00131
75	2.341807	1.650536	4.224315	8.135786	0.054424
76	1.373833	1.218549	4.404453	3.518789	0.086645
77	2.387967	0.970353	2.622647	0.4331	0.012402
78	3.69706	2.314453	2.495583	1.35198	0.157844
79	2.048236	0.345164	7.560871	0.68972	0.287151
80	1.232316	0.771233	3.48061	0.250667	0.114368
81	2.377651	1.082367	1.309008	1.270064	0.04091
82	1.524173	0.92216	0.48145	2.586355	3.37E-05
83	2.456342	1.962042	3.4929	0.018313	0.011583
84	1.549747	0.689055	2.7347	3.451802	0.007375
85	3.156278	1.57455	4.952405	0.58154	0.25429
86	1.51482	0.947102	2.798225	5.095856	0.011941
87	1.22344	0.634217	1.679189	1.951847	0.01075
88	3.13038	2.546687	1.536081	1.334502	0.044289
89	1.883987	0.319309	1.641699	4.67575	0.243068
90	1.80192	1.281761	3.069954	3.532343	0.53727
91	1.174805	0.604386	3.835681	1.310704	0.231556
92	3.812293	2.646447	3.104749	0.150072	6.75E-06
93	4.947236	4.420927	6.633271	1.546701	0.02274

94	2.661698	1.915189	3.881746	1.757908	0.432592
95	2.413682	1.01524	2.437705	2.108054	3.23E-05
96	1.895441	1.005899	4.337535	0.85781	0.58547
97	3.358383	2.728362	4.236304	0.321262	2.62E-06
98	1.528248	0.12443	4.313073	3.231526	0.028024
99	1.723605	0.983987	1.644835	0.575192	0.241524
100	1.615987	0.274867	2.097438	0.98715	3.38E-05
101	1.071288	0.068132	4.228603	1.678937	1.463895
102	3.00178	2.345166	0.919553	1.974653	0.023078
103	1.50452	0.912942	1.70934	6.152906	3.29E-06
104	1.188306	0.788702	3.278564	5.36283	0.141604
105	3.88056	3.402384	6.647913	3.155478	0.36155
106	1.643434	0.771098	4.022716	0.375959	0.002553
107	1.350238	0.411222	0.525564	0.259764	1.491592
108	1.73698	0.443286	0.881462	1.231375	0.002985
109	1.143027	0.453789	0.962565	1.512054	0.091824
110	2.119251	1.568061	1.119393	4.143332	0.238043
111	3.109874	2.241966	2.788314	0.951375	0.034179
112	1.612118	0.428117	3.319973	2.464322	0.692932
113	2.55881	1.862019	2.218435	0.312174	1.482744
114	4.232879	2.822717	4.895716	2.046329	0.075251
115	1.876807	1.020479	0.479625	0.31191	0.033073
116	1.050749	0.428436	2.551911	2.12534	0.143562
117	1.841118	0.774999	0.599265	0.141871	0.353732
118	1.493719	0.879379	2.70993	4.172097	0.505386
119	1.286873	0.250692	5.47713	0.297115	0.47271
120	5.006769	4.106294	1.10544	1.261975	0.074739
121	2.758153	1.674876	6.279542	3.375803	0.058924
122	2.93471	2.492805	4.167914	1.136182	0.009403
123	2.777804	1.45565	1.698214	5.345734	0.003059
124	2.127037	1.277009	7.747109	0.570172	0.013114

125	0.610755	0.218075	3.995914	0.357982	0.009795
126	5.602819	4.903193	0.865617	0.045029	0.811383
127	3.030768	1.600274	1.684926	1.183446	0.034969
128	2.498129	1.412565	2.634403	1.011182	0.051846
129	2.396812	1.526051	2.5992	14.16525	0.063598
130	3.100553	1.947863	0.845226	3.46866	0.015014
131	1.223574	0.455319	0.29853	0.275103	0.015553
132	5.10701	3.498951	0.517571	0.637195	0.345385
133	1.823926	0.750433	1.884589	1.637428	0.243106
134	1.282786	0.398469	2.019867	1.574855	0.321787
135	2.876613	2.261914	1.640008	1.740034	0.344669
136	1.88677	0.634792	5.231978	4.088434	1.118116
137	2.171732	1.015328	4.712038	1.820474	0.421804
138	2.322505	0.97076	1.849508	0.970533	0.007695
139	2.368297	1.646232	0.315782	2.57812	0.203837
140	1.859125	1.119771	3.685774	2.006036	0.007704
141	2.010222	0.528803	3.899109	4.370394	0.016197
142	1.005207	0.282108	1.5971	2.177927	1.51528
143	4.097499	2.571541	1.656996	0.550981	0.063586
144	2.429105	1.263395	3.33561	2.334999	0.010024
145	1.523488	0.731179	1.47903	1.054003	3.01E-08
146	2.487742	1.167762	0.973021	1.537142	0.023288
147	0.684256	0.032529	0.312092	0.353407	0.000733
148	4.167945	2.96749	0.126836	5.97342	0.233371
149	2.28007	1.750708	3.457396	2.98099	0.000138
150	1.890688	1.940626	3.271626	1.858445	0.075451
151	1.527735	0.975954	2.795716	1.720618	0.267327
152	1.482023	0.437391	0.920774	1.381556	0.084325
153	0.550028	0.116353	2.295018	1.166107	0.198605
154	1.832147	0.342816	1.186663	3.621163	0.002175
155	3.037375	1.834614	2.577983	0.157868	0.000432

156	1.852636	0.937553	3.961909	2.066527	1.67E-06
157	3.849299	2.642313	2.981286	2.632547	0.02263
158	2.580792	1.413971	2.554658	0.267372	0.010814
159	0.792734	0.354327	6.295937	0.408042	0.129457
160	1.354121	0.284337	0.447748	3.13954	0.017581
161	2.604087	1.512381	1.125633	0.051252	6.96E-05
162	4.801916	3.625755	4.524376	2.870269	6.23E-05
163	3.561791	2.333909	0.61592	1.516638	0.000311
164	2.946432	2.050848	0.783033	0.793243	0.98831
165	0.421695	0.268307	0.607416	5.086127	0.001414
166	2.139515	1.5072	0.193861	0.599152	0.244381
167	3.739684	2.11719	2.313099	0.730835	0.006329
168	3.662154	3.027943	7.353304	0.91564	5.80E-06
169	1.390962	0.107273	2.146445	1.320115	3.70E-05
170	2.877186	2.281776	7.414177	4.314189	1.55E-06
171	1.806064	0.590079	2.20881	3.829454	9.68E-06
172	2.367805	1.304203	3.386382	0.084902	0.010822
173	1.034666	0.9563	1.512057	9.024626	6.17E-14
174	2.41338	1.433903	2.344379	0.696751	0.01157
175	1.970074	0.993134	4.542853	0.047229	7.14E-08
176	1.261606	0.106403	0.320674	1.046699	1.01364
177	1.510257	0.665079	2.354313	2.101819	0.085062
178	1.891194	0.023442	1.961587	1.334074	0.200688
179	4.72551	3.018758	1.959137	0.03643	0.031388
180	1.456791	0.18365	2.421369	0.136287	0.076375
181	0.899026	0.101967	1.113149	0.729821	0.794669
182	1.315742	1.247919	0.520092	1.703575	0.066617
183	3.197936	2.201822	5.181671	1.257239	0.315402
184	2.132572	1.160663	0.731989	0.438147	0.019802
185	1.853242	0.772866	2.774452	3.664853	0.116719
186	2.357996	1.649245	3.673572	0.121149	1.11E-05

187	2.376892	0.987717	4.789498	0.282387	0.005873
188	1.05351	0.701856	0.062694	1.194749	0.187758
189	1.846864	1.234632	1.721083	0.804372	0.027211
190	4.030429	2.401986	4.602821	0.170528	0.013422
191	3.32402	1.403283	0.460041	1.123789	0.098343
192	2.906207	1.96994	1.682399	0.415285	1.32253
193	3.252799	2.484209	1.57767	3.524319	0.081438
194	1.353777	0.763452	6.32011	3.084146	0.093396
195	1.929152	0.824789	0.678384	0.832812	0.060479
196	1.522394	0.941059	8.869172	0.533833	3.11E-07
197	2.102255	1.174698	4.151109	1.860736	4.55E-12
198	2.428378	1.492912	2.707795	0.649313	0.00631
199	2.754512	1.192275	1.409605	1.849826	8.22E-08
200	3.528913	2.270127	1.497251	6.24635	0.014825
201	1.672306	1.006599	0.390719	0.532097	0.000139
202	2.942896	2.156118	6.428708	0.382876	0.417211
203	3.238514	2.414873	2.291569	3.857909	2.947625
204	2.019347	1.003761	0.77609	1.999395	0.047319
205	1.453967	0.207485	1.123218	1.178464	0.134461
206	2.117191	0.846954	1.035693	2.052525	1.451366
207	6.943197	5.626215	2.657711	1.023544	0.007731
208	1.484018	0.382776	7.481627	1.213974	3.91E-05
209	3.666963	2.382906	6.875599	0.627692	0.000713
210	4.448204	3.543214	7.047899	0.563554	0.000276
211	1.476683	0.085222	1.939346	0.469304	0.139929
212	1.657295	0.39401	0.080697	3.231985	0.087996
213	3.155362	1.745163	1.889078	0.640666	1.29E-06
214	3.384452	1.618392	2.995011	1.867129	0.004406
215	1.011156	0.824555	1.239234	1.492586	0.015013
216	1.79942	0.753232	22.49321	4.763583	1.01E-06
217	2.827585	1.910673	2.154879	3.993863	0.862146
218	1.120486	0.769559	1.784882	1.075646	0.007461

219	3.489617	2.586993	3.45835	1.986839	0.103637
220	1.398887	0.394642	2.801503	0.780337	0.189969
221	5.263581	3.786851	0.51086	0.656838	1.092748
222	1.613547	1.061771	0.583498	3.356934	0.140237
223	0.711189	0.148343	0.010899	1.301582	0.018962
224	1.076352	0.128876	2.130112	0.454949	0.391148
225	1.034904	0.388493	2.853135	3.835818	6.92E-06
226	3.598222	2.853485	4.296221	2.626808	0.275541
227	2.941165	2.106302	4.542505	5.194792	0.002976
228	2.179022	1.851158	3.078277	1.769221	6.23E-05
229	1.90259	1.026817	6.566862	0.094403	0.003595
230	1.875313	0.734378	1.608273	0.496916	0.071354
231	0.925921	0.287573	2.250702	0.070939	0.00793
232	2.586067	1.629711	4.910614	1.206401	4.51E-09
233	4.195051	3.146492	4.377308	0.912125	1.190042
234	2.519463	1.504503	2.782767	0.286403	6.79E-05
235	6.975923	5.905045	3.55825	2.188427	0.041702
236	4.342303	3.46584	3.65586	0.052462	0.606066
237	1.594205	0.825932	5.77136	1.211169	0.020051
238	2.050763	0.76103	2.247146	1.834834	0.427026
239	2.066423	0.929815	3.822944	0.870848	0.017588
240	3.466664	2.226117	2.502217	1.030936	0.001577
241	1.206234	0.522284	7.998881	0.255218	0.061732
242	1.912754	1.014891	2.536442	3.150176	0.007332
243	2.246976	0.653714	0.720682	2.669399	0.00051
244	1.318009	0.181388	4.701163	3.846645	0.017535
245	2.319374	0.270735	4.4592	0.077583	0.000368
246	3.97969	3.019015	7.260344	4.869737	0.046074
247	3.59165	2.44136	0.284981	0.08449	0.004051
248	2.517489	1.070761	1.122527	0.861212	1.38E-06
249	4.677499	2.882446	6.080138	1.283965	0.01319

250	1.766972	0.510828	1.614297	0.300727	0.000782
251	2.745796	1.779129	3.849865	1.988632	0.220836
252	2.777505	1.285348	3.718731	0.087878	9.47E-05
253	2.177336	1.547059	5.912897	2.874846	0.000507
254	1.285037	0.39881	0.9552	0.304024	1.25E-05
255	6.672952	5.65299	5.835193	4.114368	0.001515
256	2.876235	1.216857	2.455576	0.330518	1.89E-09
257	1.178626	0.358824	1.284859	0.083781	0.308431
258	1.454701	0.766417	5.89859	6.675398	1.20E-06
259	5.000933	3.957319	1.181106	2.534086	2.92E-05
260	2.300249	1.206116	5.556148	0.52579	0.489946
261	1.575482	0.601753	3.174451	2.97405	0.845961
262	2.844834	1.828493	1.95913	0.385829	1.237987
263	3.632837	2.769739	1.368024	2.508518	4.14E-13
264	1.991346	1.261723	4.537959	1.259597	1.99E-08
265	4.101725	3.486852	3.432959	3.79872	0.112425
266	2.515771	1.35661	9.748527	0.128306	0.021913
267	3.123774	1.494376	0.593592	3.735647	0.01474
268	0.955537	0.4723	0.812432	1.560628	1.24E-06
269	1.409653	0.135609	2.059624	0.284942	0.455904
270	2.399029	0.586491	0.409603	0.16532	1.361396
271	5.389817	4.101543	0.802043	3.069169	0.009564
272	2.258139	1.812442	5.51078	4.596048	0.471133
273	0.507193	0.519688	3.233966	7.121888	3.86E-09
274	2.687583	1.479179	0.843845	2.384521	0.047744
275	1.081685	0.185094	1.766609	1.013957	1.329389
276	3.391357	3.022353	8.939503	4.831425	0.342609
277	2.862061	2.25384	2.004445	1.529718	0.094057
278	1.851898	0.486387	1.461575	1.12025	0.154725
279	1.34105	0.519144	2.973368	3.914494	0.254876
280	2.659683	1.479997	7.432742	2.657004	0.118844

281	3.276163	1.872332	0.911167	2.779548	0.009803
282	2.016048	1.800376	4.230342	0.108974	0.196372
283	0.790709	0.368285	6.597011	0.915319	0.026493
284	5.028983	3.632763	3.394562	3.077963	1.397116
285	1.29058	0.247085	2.640514	0.603141	0.778193
286	3.357505	2.13442	4.099482	3.803171	0.000209
287	1.139665	0.288031	2.262611	1.143536	0.055954
288	4.635238	3.415676	6.463943	0.665118	0.116691
289	1.538216	0.798941	10.62455	2.371486	0.14195
290	3.927967	2.411984	4.953136	2.819357	0.000147
291	2.03796	0.279024	5.401557	0.953176	0.052296
292	2.871875	2.317662	0.390126	1.579402	0.001135
293	1.324381	0.475296	1.422716	0.432814	0.104364
294	1.633922	0.296705	2.593279	1.474272	0.042138
295	1.021537	0.267619	4.650909	1.363003	0.028489
296	1.312876	0.717811	4.78705	1.482302	0.001552
297	1.761631	0.646095	0.572685	1.208487	0.003427
298	7.171308	6.83778	1.276036	4.405034	1.205438
299	1.674752	0.564057	2.552533	2.002996	3.22E-07
300	0.839745	0.074952	0.923331	9.845991	0.32631
301	1.491176	0.168148	11.24251	5.790785	2.30E-06
302	2.1685	1.442197	3.252523	3.081904	0.003782
303	1.880653	0.755056	2.220034	0.042121	0.032264
304	0.850662	0.394798	2.487173	1.998208	0.762258
305	4.617567	3.991574	2.278716	0.655688	0.000353
306	3.036293	2.116378	4.228948	1.024693	0.265372
307	0.605246	0.169383	1.330984	0.297794	0.104866
308	1.434418	0.742456	2.649117	0.837602	0.825132
309	2.440029	0.641543	2.507321	5.461919	0.000306
310	2.809188	2.321592	1.394922	2.819813	0.000177
311	3.785923	2.409871	12.52072	0.286079	0.014955

312	1.827901	1.469673	0.430059	2.78386	0.000569
313	3.161009	2.677186	3.770796	0.25782	0.432572
314	1.766648	0.620718	0.128244	1.967894	0.062858
315	3.030138	1.050236	4.471962	4.670145	0.040398
316	2.523526	1.294897	2.096842	5.575098	0.001511
317	4.183907	3.212112	0.596545	0.62595	0.020115
318	3.627036	2.616713	3.555104	5.860276	0.032874
319	2.199888	1.355342	1.187243	0.023151	3.11E-07
320	3.015584	1.880251	2.574084	1.886021	0.002464
321	5.594655	4.845346	2.438315	0.246426	0.119193
322	1.571619	0.765489	2.94529	1.889541	0.000162
323	2.678683	1.661478	0.317733	0.871485	0.268498
324	1.516786	0.028884	1.414909	1.633789	0.386986
325	4.43245	3.037017	4.431456	5.744854	0.001297
326	4.039503	3.832354	1.145805	3.249004	0.009176
327	1.647705	0.765937	0.276962	1.683914	0.022115
328	1.729839	0.77871	0.412442	4.482251	0.000154
329	1.342718	0.088725	3.447785	1.314387	0.000106
330	2.891285	1.646142	1.912265	3.526617	1.57E-08
331	1.44977	0.503595	1.482219	0.016641	0.007349
332	1.443606	0.342696	6.273871	3.135239	0.060827
333	3.260918	2.696223	2.998322	0.425773	8.52E-08
334	3.272177	2.513257	11.38584	0.640628	0.840494
335	2.892341	1.977713	7.577964	1.714655	0.018714
336	1.990393	0.396591	0.892865	1.312456	0.000852
337	1.690917	0.194236	3.281158	1.812536	0.045574
338	1.998112	0.944251	7.2188	5.294472	0.000333
339	2.814665	2.346712	1.007215	1.417147	0.089795
340	1.18238	0.530555	3.176051	3.041678	0.042827
341	1.546821	0.389982	1.016485	1.276054	0.139745
342	4.763666	3.925347	0.7124	0.33813	1.647593
343	1.960088	1.142049	3.660196	1.150579	0.400916

344	2.811861	1.399232	5.655039	0.660621	0.333513
345	2.519417	1.267321	2.896769	0.578262	0.023465
346	0.845817	0.181669	1.804799	0.151786	0.306865
347	4.753489	3.410902	4.8902	0.72023	0.102735
348	2.534769	1.578857	5.250952	0.529788	0.000254
349	2.498707	1.729082	2.446339	10.16295	0.067381
350	0.832136	0.637421	2.647671	1.694103	0.002712
351	3.488248	2.567414	4.564323	1.00126	0.005463
352	4.227249	2.793873	2.150381	1.872455	0.001897
353	2.741191	2.170247	5.433367	0.215127	8.35E-10
354	1.876289	1.077676	2.132288	2.895158	0.062355
355	1.09377	0.090302	6.00869	0.056377	0.181848
356	1.152278	0.335426	0.825084	4.99047	0.000147
357	4.486898	3.215743	3.580369	4.193258	0.664885
358	2.822548	1.450794	2.488152	7.633562	0.684279
359	1.507326	0.232453	1.291893	0.346686	0.390764
360	2.383544	0.679509	5.542457	0.897499	0.019443
361	1.893607	0.090478	4.357788	1.525201	0.000113
362	1.895908	1.02605	1.354497	1.434468	1.68E-08
363	3.616123	2.682162	0.782151	0.257816	0.041668
364	1.691996	0.40132	2.940557	5.98509	0.24537
365	1.136765	0.378052	1.995287	0.55662	1.17E-10
366	4.479004	3.27199	0.969018	4.231266	0.400692
367	7.114914	5.516358	1.901809	0.281842	0.006955
368	1.897763	1.169323	2.260408	0.637596	0.284398
369	2.285764	1.591986	2.155188	0.334031	0.10118
370	3.241056	1.967507	4.100265	2.852939	0.018591
371	1.306348	0.40741	6.246284	1.038863	1.78E-05
372	1.428628	0.517487	2.261232	0.241075	0.043056
373	3.325543	2.550634	1.177748	0.376228	0.018283
374	1.688871	0.557002	4.416175	8.782099	1.04E-06

375	2.687067	1.939711	0.512286	0.00644	0.001779
376	3.433991	2.219037	1.886831	1.828222	1.63E-06
377	1.203346	0.251752	5.171076	0.329169	6.69E-05
378	1.046171	0.355688	1.136154	7.902616	0.056627
379	2.76806	1.677679	3.223024	0.707771	0.003759
380	1.590583	0.223724	0.04853	1.042111	0.442993
381	1.285033	0.250295	5.392613	0.26642	0.000133
382	2.370633	0.951132	3.562545	0.399212	1.215691
383	1.274515	0.296082	5.303951	1.598539	5.25E-07
384	5.594762	4.706389	3.963344	3.782436	5.89E-07
385	1.796339	1.001368	7.30866	0.019188	1.27E-05
386	1.870872	0.962858	1.845268	3.315658	0.002019
387	1.058908	0.015272	4.869205	4.692048	0.610594
388	1.262316	0.434619	3.379	0.754605	0.00011
389	4.968237	3.328703	1.985004	0.810456	0.451604
390	3.476389	1.952127	1.28488	0.224866	0.292578
391	0.75064	0.26392	2.846894	0.329543	0.002603
392	3.776741	2.074595	0.119513	0.522059	0.257748
393	2.387268	1.322961	16.71646	2.267363	2.387138
394	3.543008	2.208074	0.384383	0.076881	0.339165
395	1.735006	0.707881	4.016116	0.610288	0.001365
396	2.759922	1.444796	5.573895	5.426386	0.190556
397	1.704413	0.745182	7.422386	7.042058	6.85E-06
398	3.163282	1.805193	6.047105	0.599619	4.95E-06
399	1.398576	0.544461	0.267667	0.611292	0.096752
400	1.523559	0.3402	0.89259	1.15088	0.07405
401	2.304362	0.971604	2.159368	1.720983	0.441363
402	3.592462	1.871028	1.843846	0.207822	0.066532
403	1.124064	0.537601	3.570746	0.159471	0.235583
404	2.175947	0.839495	1.642327	1.816464	0.015257
405	0.957114	0.363905	11.18917	1.014265	0.056611

406	3.051893	1.916768	9.966304	4.90869	0.028245
407	2.898241	1.551577	0.715483	0.023386	0.138938
408	1.920466	0.766244	0.999592	3.19689	2.89E-05
409	3.659096	2.377526	2.483735	0.139056	0.006914
410	1.623726	0.183078	2.321418	5.079229	0.004954
411	1.584112	0.450039	1.720151	0.051109	0.000545
412	1.86648	1.132078	1.524256	0.603358	0.054345
413	1.527763	0.592456	3.105811	0.171428	0.009332
414	2.02861	1.369843	4.642949	1.045729	3.90E-05
415	4.010388	3.110219	0.309348	4.027914	0.01525
416	2.174845	1.017644	0.283802	0.339055	0.110491
417	2.362255	1.138005	1.628256	0.661175	2.11E-05
418	1.536139	1.021348	2.748219	11.4835	7.75E-05
419	4.18375	2.981591	3.557158	1.126747	0.854239
420	0.932076	0.070363	5.190349	5.473094	0.023453
421	1.121543	0.554434	3.930955	2.007199	0.001341
422	1.538878	1.345161	2.890419	0.662343	0.662532
423	1.470795	0.829076	5.858887	0.127027	0.00033
424	1.69322	0.645417	0.397284	0.336213	0.011243
425	3.909996	2.045635	3.38487	2.622897	0.20279
426	0.762285	0.190319	2.847324	4.004107	0.14154
427	5.453241	4.365827	1.068448	1.218498	0.642398
428	3.447626	2.255801	2.710304	4.896019	0.001091
429	1.878429	0.162178	2.716883	0.0159	0.000514
430	1.586148	0.712784	4.905169	2.872016	0.013815
431	0.279812	0.034551	4.060912	9.000559	1.527467
432	1.849746	0.940846	0.238156	0.799816	0.012658
433	0.698641	0.100321	0.875132	0.550347	0.092418
434	1.981341	1.353028	0.864683	0.196399	0.181752
435	2.284837	1.470412	3.248126	8.457181	0.000331
436	2.197575	1.084705	2.414525	1.020768	0.005149

437	2.132302	0.558456	0.498923	0.854858	0.061191
438	2.15787	1.516244	1.401066	1.512962	0.261183
439	3.431131	2.682995	6.118055	0.104605	9.09E-07
440	1.568926	0.548937	0.710824	0.951274	1.368782
441	2.803292	1.462023	1.818978	4.560261	0.230742
442	5.69749	4.370652	3.428661	0.413734	0.325394
443	3.404262	1.96695	2.788589	0.750487	0.375923
444	2.296058	1.417417	5.484341	0.845007	0.061647
445	1.575239	1.075892	0.816875	2.070299	0.234501
446	0.491946	0.41605	2.181372	1.131996	0.451395
447	1.766796	0.701816	0.605819	0.517251	0.160323
448	1.963058	0.565727	2.568115	8.86208	0.495106
449	7.187127	6.193462	0.618114	0.999047	0.442537
450	2.098561	0.653161	0.290025	1.44284	0.050231
451	1.491624	0.276139	3.721895	4.522223	0.469276
452	0.331564	0.090649	5.321202	5.879283	0.056766
453	2.794736	1.848652	1.467429	1.817815	1.829545
454	5.248655	4.60525	1.862868	3.5626	7.65E-07
455	1.654115	0.602916	2.954091	1.019084	0.152181
456	3.527866	2.343998	1.531608	4.129417	1.45E-07
457	0.517357	0.074479	3.496786	2.084916	0.000204
458	3.367105	2.330603	0.822988	1.496271	0.009501
459	5.389271	4.126005	1.459298	2.288201	0.095045
460	0.658127	0.433389	1.602997	0.058242	0.00467
461	0.815237	0.517679	6.377971	2.890928	0.689086
462	2.029257	0.291146	1.559133	5.045071	4.83E-05
463	2.288575	0.799569	4.031147	0.695237	0.263041
464	2.629471	1.878907	3.46282	1.055788	0.000325
465	2.654163	1.925439	2.726051	5.924777	0.000331
466	1.120403	0.14231	4.076703	1.314465	0.078378
467	3.26097	2.412338	1.482605	0.098004	0.21901
468	3.175833	2.315094	1.593697	0.159361	1.355877

469	2.823843	1.262687	0.333806	1.285749	2.506364
470	2.759445	1.331497	2.011243	0.946674	0.196599
471	2.079282	0.942054	1.95933	0.602165	0.010265
472	2.224902	0.87843	1.002571	1.952191	3.95E-12
473	1.718979	0.499422	0.734893	4.072772	0.001133
474	1.789686	0.736917	3.373708	0.946264	0.218508
475	4.464441	3.010444	3.780197	9.351681	0.000629
476	2.61824	1.015865	3.920399	1.389203	6.21E-06
477	1.385415	0.318709	1.497109	0.104948	0.163478
478	1.637106	0.854622	2.029632	0.360761	0.001004
479	3.220422	2.531476	3.212662	0.475201	0.98925
480	1.112793	0.192196	3.178734	1.170282	0.189572
481	1.224372	0.313837	1.382448	0.394453	2.54E-07
482	0.725134	0.626598	9.203803	1.464855	0.0015
483	1.884961	1.113429	3.207568	0.8943	0.00609
484	1.102348	0.630365	1.578453	0.50762	0.466938
485	3.190311	2.323411	3.774848	2.408847	0.000338
486	0.675354	0.025176	0.547619	0.611712	0.007028
487	2.332719	1.491891	3.147428	0.767285	0.00164
488	1.903364	1.193972	2.439845	3.591289	0.010621
489	1.745797	0.759137	1.383252	2.418645	0.006951
490	2.20787	1.875697	3.655486	0.531274	0.044612
491	3.82104	2.69367	0.697709	2.580835	0.000993
492	1.416944	0.476469	8.677496	1.78545	1.53E-05
493	0.80165	0.132589	0.872697	0.47204	0.000531
494	2.801462	2.001434	3.699479	0.683501	0.241624
495	4.864119	3.560987	4.404044	0.845973	0.000102
496	2.104832	1.566783	6.196837	1.073263	0.152472
497	3.19488	2.078432	2.150724	0.125761	0.071364
498	4.902131	3.427556	0.378027	2.361133	0.000192
499	3.222945	1.886166	2.444131	10.75964	1.34E-06

500	1.785685	0.344744	1.007072	0.447643	0.162534
501	2.178281	1.271473	10.79597	0.401127	0.071553
502	2.046039	1.568572	0.910877	8.11168	0.029464
503	3.884184	3.77535	6.760993	1.358414	0.043531
504	1.162273	0.271782	0.439866	1.744145	0.185201
505	2.715658	2.029844	3.74439	2.023233	0.036042
506	2.829275	0.913642	1.499306	1.205551	2.05E-08
507	2.190157	1.609903	9.212508	1.620611	0.151477
508	3.239489	2.151113	4.624578	0.479196	0.000912
509	1.42751	0.455925	1.718271	2.631935	0.243902
510	3.420195	2.534399	3.28617	1.195626	0.066078
511	1.443954	0.923374	7.756422	14.94431	0.075463
512	1.101415	0.047603	1.735318	3.155789	0.000514
513	4.09463	2.994307	6.014124	3.171938	0.134228
514	1.341814	0.225613	6.12025	0.716866	0.021595
515	1.994527	0.381063	3.257466	3.857314	0.003137
516	1.809311	0.369452	3.689012	2.077833	0.086262
517	2.305905	1.662346	0.306798	1.064938	0.000589
518	5.102357	3.291531	9.503868	5.433995	1.06E-09
519	3.574939	2.343014	1.223179	8.963232	0.035635
520	2.399339	1.534189	2.891072	1.069446	0.022032
521	3.681989	2.8401	0.568291	0.166979	7.29E-05
522	1.269048	0.452337	1.703995	4.206631	0.082817
523	3.939923	3.189636	0.164428	2.402432	0.000406
524	3.230227	2.062068	1.803299	0.793288	0.223561
525	1.243493	0.51038	5.792793	2.062862	0.634152
526	3.678592	2.250085	2.888258	0.438794	0.004895
527	0.968187	0.454281	2.571392	0.446254	0.545153
528	1.891754	0.588469	1.274178	0.099917	0.033616
529	5.584129	4.809727	1.204896	0.377302	3.85E-07
530	3.140257	1.93169	1.106016	0.694532	0.006306

531	2.996374	1.282081	0.498555	6.20429	0.002557
532	2.970813	2.669214	0.695906	0.092451	0.000686
533	1.033576	0.543674	2.675177	1.62248	0.000605
534	3.58314	2.542412	2.510372	0.448931	0.041716
535	2.688998	1.915123	3.742876	1.73337	5.07E-05
536	1.553161	0.515571	4.612813	0.655247	0.019734
537	1.0778	0.219123	3.349878	2.3255	4.12E-05
538	0.999483	0.301588	3.456909	3.265374	0.120088
539	3.651861	2.611431	3.005123	0.798655	0.00119
540	4.624038	3.178713	1.036	1.490295	0.001069
541	7.58577	6.128373	1.199862	0.348497	0.008416
542	2.609879	0.940871	3.277313	0.632624	0.430289
543	0.836861	0.179917	1.043068	1.567834	8.33E-06
544	2.252463	1.647352	6.033096	1.059686	0.000933
545	1.598982	0.39105	4.166542	0.496038	0.05444
546	1.543854	0.287567	4.591426	0.249009	0.280004
547	2.823655	1.113873	1.203035	9.9013	0.32488
548	3.443112	2.189253	2.370671	1.87319	0.000674
549	1.183616	0.11789	4.405828	4.086511	0.047006
550	5.343309	4.274009	5.842993	0.144145	0.004227
551	1.562686	0.094473	0.413135	1.363749	0.004419
552	4.864271	3.16723	5.464024	1.373153	0.006203
553	2.172352	0.800759	2.000957	0.266168	0.142434
554	2.932802	1.576953	3.717163	2.104503	0.969184
555	1.55329	0.792414	3.940832	3.286376	0.017753
556	1.108206	0.420362	1.144623	2.615155	0.001803
557	2.425414	1.132375	0.194215	0.544161	0.025318
558	1.580962	0.615801	4.54686	0.226646	0.009936
559	2.055444	1.125194	5.382042	8.854355	0.00261
560	5.547538	4.25047	6.067432	0.28448	0.14248
561	1.378606	1.150693	4.246991	1.352007	0.308769

562	2.566803	0.964072	2.359029	2.118886	0.169623
563	1.785484	1.084062	4.506313	4.458915	0.708153
564	1.950676	1.418533	0.219904	0.112434	0.000182
565	2.899647	1.490641	4.802337	1.306749	0.097411
566	3.216072	1.865412	2.132729	1.106096	0.005812
567	3.481522	2.136511	0.200784	1.049619	0.39201
568	3.551935	1.957745	5.860412	0.422749	0.139613
569	4.956746	3.562722	1.988957	1.727303	0.011311
570	2.75425	2.090822	2.778431	3.692216	0.000238
571	1.932955	0.427887	0.699707	0.78343	1.226171
572	1.955163	1.344707	0.715098	1.115993	0.000479
573	3.523647	2.426497	7.550666	1.549078	1.15E-05
574	2.425345	1.56814	1.089414	1.238911	0.544017
575	1.615339	0.267221	0.675175	3.856472	0.003615
576	0.732437	0.348463	3.625874	0.551207	2.54E-06
577	3.548907	2.406158	9.133953	2.528748	0.075969
578	2.550025	1.83646	0.510085	1.940439	0.057329
579	1.342516	0.230301	1.1327	0.181837	0.394927
580	1.693462	0.786868	1.704965	0.098704	0.323027
581	1.607784	0.198492	1.255284	4.785982	0.297667
582	1.633561	0.636286	0.474618	0.594407	0.017083
583	2.622623	1.145044	5.562055	0.402354	0.101908
584	1.712006	0.640207	2.108985	0.101898	1.046377
585	3.523039	2.628963	2.685252	0.431064	0.058317
586	1.464679	0.787297	2.339792	1.648815	2.24E-06
587	1.494188	0.52683	2.745128	0.491525	0.18039
588	1.934703	0.131205	0.874727	0.863611	4.77E-07
589	4.083587	3.24578	1.219089	1.74126	0.516182
590	2.728297	1.841119	0.85504	1.666962	0.029349
591	1.289745	0.401751	5.334528	2.215647	0.043042
592	4.462669	2.803833	1.665968	2.244561	0.00015
593	2.550797	1.035876	1.814791	0.504247	1.01E-10

594	2.793303	1.97034	0.912035	0.217627	0.198396
595	3.899849	2.817507	2.341607	5.229207	0.093068
596	2.936616	1.245079	5.740896	0.561703	6.58E-05
597	1.188688	0.378343	5.796373	2.7891	0.008653
598	2.646617	2.162313	0.829336	3.62677	0.173765
599	1.627912	0.417327	3.395029	2.09814	1.76E-06
600	0.371984	0.149138	1.522079	0.285435	8.01E-09
601	1.554133	1.237488	4.814824	6.324571	5.41E-05
602	2.394527	0.692371	4.592983	3.054714	0.024827
603	2.356507	0.8141	3.909001	5.734383	0.032891
604	1.150609	0.115512	2.097939	1.725073	0.035902
605	2.196685	1.231645	0.427542	2.124012	0.450238
606	1.567378	0.634069	2.35689	0.138227	0.104912
607	2.187795	1.281379	0.574073	1.917636	0.010312
608	3.046117	1.78234	1.089435	6.526655	0.02879
609	2.362729	1.136386	1.678291	0.667127	0.000977
610	1.483299	0.707135	0.498942	2.240345	0.127585
611	4.265427	3.348418	1.459661	0.589078	0.283812
612	1.701413	0.977457	0.144329	3.912786	0.002695
613	1.634049	0.413197	3.638561	1.181933	0.014839
614	2.385751	0.631409	0.302244	0.326416	0.024551
615	2.144713	1.047099	2.817822	5.572245	0.039705
616	2.269619	1.414517	4.349109	6.143028	0.388928
617	1.002057	0.018727	3.156719	0.81606	0.014973
618	2.093901	0.984757	1.630756	0.513812	2.40E-05
619	3.289118	2.42659	4.186754	4.69453	0.013817
620	2.963233	2.489311	0.611426	4.066528	1.306336
621	2.824742	1.406507	4.539109	1.029451	1.612181
622	3.076155	1.493432	0.161258	1.155456	0.001152
623	1.179622	0.776141	4.676323	2.809525	0.001146
624	6.162042	4.444597	2.635753	2.959689	3.19E-08

625	1.216488	0.32213	1.888912	1.204976	1.414421
626	2.0917	1.053413	3.901943	0.360514	0.014546
627	3.145467	2.402329	3.393784	4.379809	1.11E-09
628	1.89256	1.131499	1.356978	0.271412	0.431111
629	2.715294	2.061047	2.694079	1.31713	2.86E-06
630	0.798617	0.0539	2.355663	0.174987	0.008095
631	1.926415	0.820405	1.769019	0.37227	0.000612
632	2.197668	1.830722	1.216406	3.374259	0.004737
633	2.716694	1.726309	0.385286	0.474945	0.008508
634	3.762902	2.377075	2.679541	3.344827	0.002014
635	3.711713	2.374409	2.160793	0.044348	0.019036

636	1.695877	0.433114	2.995638	0.171052	0.006289
637	3.056393	2.505705	1.415832	2.430722	6.58E-07
638	1.541097	0.42418	2.111258	0.52423	1.49E-08
639	3.402	2.775047	4.369488	0.161627	2.138172
640	0.989829	0.141546	5.190853	0.381591	0.433817
641	2.540598	1.527113	8.536178	0.744614	0.249659
642	2.266298	1.081324	3.709373	0.981115	0.035445
643	2.106456	0.672664	6.457388	1.88125	1.49E-07
644	2.644138	1.257739	0.822065	1.055559	0.005855
645	1.024702	0.29792	0.446297	1.903889	0.635968
646	1.597927	1.03392	5.46904	2.16711	3.31E-05
647	1.931512	0.966954	0.306168	1.371643	0.046849
648	1.616349	0.860104	3.693761	3.400377	0.002741
649	4.970508	4.283291	0.501702	0.148098	0.008759
650	1.426244	0.720756	3.164658	3.279428	0.012586
651	4.817583	3.354734	1.175826	2.15195	0.08588
652	3.811438	2.794043	0.119101	0.628945	0.915312
653	0.526213	0.119731	4.212646	2.476486	0.007494
654	2.933994	2.326624	4.801492	2.465866	0.050982
655	1.493845	0.79495	4.129743	1.915218	0.013271

656	1.546094	0.915757	2.823838	3.754694	1.20E-07
657	2.515687	1.560037	7.241708	1.468075	6.42E-06
658	2.334941	1.814902	0.849316	4.112432	0.017456
659	1.692707	0.408923	2.28603	1.331533	6.28E-05
660	2.351057	1.774018	1.967748	2.366215	0.00027
661	2.355763	1.756531	2.287543	1.423163	0.001071
662	1.719964	0.555002	4.393439	5.196672	1.95E-05
663	0.99077	0.189031	1.598538	1.14618	0.061758
664	5.44257	4.535515	0.346079	1.271092	1.60E-05
665	1.958393	0.257005	1.472452	0.657447	0.083727
666	2.721969	1.32847	4.32223	0.669832	0.003089
667	3.891138	2.193899	4.144328	0.67465	0.057646
668	2.09868	0.805395	1.9127	2.410159	0.015522
669	2.040159	0.787836	0.449618	2.780111	0.03969
670	4.106615	3.542087	1.036085	2.199781	0.013947
671	3.58307	2.686188	4.664175	0.255398	0.014301
672	1.76644	0.735795	1.358224	2.729518	0.000368
673	1.345062	0.524762	0.836936	0.451659	0.028912
674	3.610243	2.229883	2.629128	1.876158	0.059527
675	2.24396	1.267046	0.918783	7.548832	0.024606
676	2.895233	2.016302	1.303297	1.687752	0.269027
677	2.289618	0.838806	2.649775	2.06977	0.813478
678	1.847383	1.160019	2.674555	1.641772	0.019704
679	1.041434	0.192832	1.322131	1.714006	0.002332
680	1.879796	0.667732	1.009301	0.219815	0.000399
681	3.351573	2.352719	7.666761	3.142649	0.018355
682	1.489478	0.146181	1.58827	5.679411	0.027645
683	3.964111	2.810113	5.234917	2.663645	0.112591
684	2.418921	1.798742	1.364376	0.573306	0.036153
685	4.323898	2.736336	0.888145	3.786404	0.028726
686	2.143998	0.966676	2.712037	0.620599	1.226536

687	1.62285	1.070007	5.73686	0.523183	0.003794
688	3.027616	2.003837	7.682713	0.2751	0.515379
689	0.783636	0.440911	1.452638	4.834768	0.056282
690	2.003496	0.417889	1.672986	0.184561	0.0426
691	1.970956	0.443964	4.363258	1.075925	0.206554
692	2.295418	0.48419	0.15484	0.157724	0.075931
693	2.299533	1.288192	2.624674	1.198112	6.80E-05
694	1.496271	0.977212	2.372828	1.803042	0.209393
695	1.118378	0.283332	0.723626	0.086547	0.010726
696	2.523514	1.374986	2.459242	2.108067	1.045084
697	2.035885	1.005195	1.819247	0.089182	0.460914
698	2.874159	1.121077	2.070746	0.743503	0.362449
699	1.8501	0.398379	2.810912	2.233814	0.014562
700	1.93619	1.751052	5.89901	1.35617	7.12E-07
701	2.783705	1.898989	2.484979	4.759548	0.001741
702	2.135256	1.686218	3.763469	0.273054	0.002272
703	1.467055	0.730076	5.459276	4.019182	1.36E-05
704	1.634095	0.729129	4.634293	2.145781	0.530824
705	0.53288	0.533745	7.261923	5.749637	0.126424
706	1.287228	0.199845	2.779179	5.822079	0.000177
707	1.997992	1.078452	0.253799	0.792047	0.155736
708	1.332604	0.276518	6.552508	0.592983	0.001384
709	1.673138	0.75608	0.718724	3.479575	0.216265
710	2.370642	0.283278	4.021605	2.072373	0.013324
711	1.437435	0.75698	3.035826	5.74384	0.003458
712	2.732524	1.891548	0.496433	0.299343	0.000127
713	2.937711	1.036544	2.179834	0.058641	0.006659
714	1.399808	0.112291	5.861182	2.372564	0.002163
715	1.722823	0.710765	1.439956	3.959402	0.09621
716	1.075381	0.54653	0.288983	0.070242	0.431462
717	6.521048	5.94097	1.046971	1.134707	3.25E-06

718	6.045372	4.831778	4.959209	2.301786	0.017728
719	2.163046	1.116941	0.946955	6.140024	0.008632
720	2.562396	1.945098	3.19689	0.590749	1.44E-06
721	6.303417	4.57857	2.826675	2.081395	3.04E-08
722	2.343853	0.608144	0.748534	5.167225	1.09803
723	0.773789	0.492499	8.388117	2.345846	0.022273
724	2.996821	1.6723	5.271945	0.599227	8.23E-06
725	3.520133	2.194908	0.809587	1.346365	0.087072
726	2.125722	0.932217	3.715352	0.796547	0.210675
727	1.820081	0.807918	0.602403	0.404848	5.61E-05
728	1.561424	0.991646	2.408943	1.250877	3.77E-11
729	5.127625	3.744368	0.619951	2.754153	0.016761
730	4.022967	2.86312	0.861448	1.007672	0.522196
731	2.054309	1.514802	2.865264	0.744168	0.000319
732	1.434003	0.62224	1.671823	1.590541	0.151386
733	1.368849	0.490963	3.107071	0.692686	0.006669
734	1.174532	0.286407	0.606526	5.306998	0.012291
735	1.074414	0.194254	3.287079	4.293053	0.000123
736	3.088942	1.915252	3.339386	2.09462	0.000546
737	3.111944	1.974365	1.862851	0.673553	0.026012
738	1.37532	0.521762	1.313513	0.099352	1.523738
739	3.019149	2.434195	0.929533	0.874297	0.018258
740	1.689979	0.48993	1.728262	0.687489	0.005322
741	4.94496	4.405258	13.7065	1.091183	0.000559
742	1.750824	0.685905	3.664663	0.298346	0.000156
743	1.75644	1.362602	7.259151	0.870175	0.423299
744	1.305645	0.959481	0.806483	0.857312	0.005604
745	1.381677	0.091312	0.126486	0.046697	0.591479
746	3.417661	1.918586	3.779859	1.54248	5.84E-05
747	1.042839	0.250217	2.323262	3.297756	1.67E-05
748	2.359624	1.658781	0.4914	5.966864	0.106807
749	3.640317	1.951304	1.45135	0.937351	0.126095

750	5.996376	5.098724	5.79951	7.923978	0.017616
751	1.460067	0.012142	1.707368	0.168182	0.524919
752	2.615162	2.359709	3.920462	0.723033	0.143566
753	1.451546	0.443038	0.014396	2.208246	2.94E-08
754	1.214025	0.148081	1.691686	2.231686	0.000256
755	3.106228	1.629184	0.498387	0.048957	0.145283
756	3.581818	2.837609	0.657091	1.750141	1.895414
757	3.640121	2.293857	2.837051	3.414005	0.002159
758	3.067735	2.267069	2.983754	1.014623	0.321622
759	1.18168	0.308311	7.284952	1.856035	0.739358
760	1.01186	0.372574	0.854161	2.392821	0.293436
761	2.304498	1.02566	3.529253	3.00278	4.51E-05
762	1.619014	1.158483	2.938921	5.266941	0.753233
763	2.371128	1.713091	5.705661	2.134607	0.266851
764	1.527447	0.113074	1.388579	1.5589	0.242366
765	3.758365	2.646626	2.491378	0.421599	0.294421
766	3.234197	1.555616	1.750769	0.354468	0.000148
767	3.286205	1.859834	2.207683	0.054311	0.002971
768	1.572031	0.291374	0.78897	0.625518	0.251408
769	2.15347	1.034804	2.372887	4.716275	0.014272
770	1.694596	0.38628	0.895966	3.608965	0.006044
771	4.088498	2.968752	6.041882	1.567805	0.025519
772	6.19283	5.660734	3.419382	0.857574	0.20716
773	1.388388	0.170967	1.461352	0.46264	0.0302
774	1.391328	0.64607	2.518444	2.157242	5.11E-10
775	2.954975	1.688379	1.625198	2.488248	0.154753
776	7.14403	5.858074	3.237343	0.362775	0.373898
777	2.576157	1.307035	12.61419	2.157902	0.010134
778	0.801993	0.347414	7.37664	0.602319	0.234831
779	1.207091	0.480735	4.075134	4.018776	0.604807
780	0.315758	0.235349	1.67502	0.564825	0.131056

781	2.958099	1.752114	1.76125	1.46495	4.43E-07
782	1.383234	0.491029	0.916082	4.916803	0.000529
783	2.603429	1.877883	2.981661	0.049052	0.012834
784	2.215551	1.266036	7.675199	7.214226	0.065558
785	2.056887	0.971472	2.372151	3.332446	0.007692
786	1.754469	0.62685	0.323039	1.188601	0.001206
787	2.019501	1.225498	1.861536	0.820429	0.065345
788	3.402923	1.645064	7.933577	2.540037	0.224375
789	1.628699	0.99002	5.036804	0.110487	0.14725
790	5.316951	4.639262	9.263493	0.390062	0.004317
791	1.994907	0.799757	0.852779	1.013687	0.221673
792	1.417241	1.087582	2.318571	2.869075	0.35354
793	0.724946	0.222365	6.851431	0.700691	0.525165
794	0.953338	0.15784	2.001974	0.035347	0.022214
795	2.695508	2.036118	2.330013	0.658536	0.018771
796	1.590204	0.33473	1.821689	2.13475	0.013332
797	2.446785	1.330116	3.877318	0.709442	1.31E-07
798	2.545292	1.28441	2.366379	2.589174	0.478255
799	0.943775	0.377381	1.801833	0.793193	2.67E-09
800	3.067142	2.095077	14.36471	1.619289	0.004689
801	1.764374	0.843364	2.633094	0.826224	0.005426
802	4.148232	3.201826	3.020663	0.936132	0.001409
803	2.69277	1.28228	1.400026	4.334397	5.24E-05
804	1.473201	0.256028	1.870244	0.496724	0.005479
805	3.251068	1.876393	3.303458	2.152773	0.051206
806	0.94589	0.048156	0.809562	0.045396	0.894993
807	3.214224	2.139032	1.704696	3.683559	0.004193
808	0.760177	0.252985	5.874618	4.992897	0.310642
809	3.049428	2.219379	2.990451	0.045919	0.011272
810	3.96049	2.962826	1.730824	0.320388	0.595753
811	2.344921	1.060939	2.936294	0.741028	0.135107

812	1.648153	0.62877	5.829094	3.159954	0.05265
813	1.536874	0.182714	2.45339	2.499827	0.564302
814	1.864986	0.687773	0.393848	0.305071	2.103588
815	3.603761	2.131628	0.692081	0.086539	0.180931
816	0.298834	0.12029	0.571664	0.124015	0.004253
817	3.452722	2.246607	3.429481	1.169285	0.06721
818	4.518513	2.850074	2.402144	2.024902	9.85E-05
819	1.991868	1.107566	3.909282	2.144176	0.00388
820	3.766384	2.819964	2.627858	8.226881	8.19E-05
821	5.632313	5.167635	1.671722	3.36817	2.21E-10
822	3.285913	2.336575	0.135336	0.594263	0.003123
823	2.60955	1.377305	0.549156	1.62224	0.257734
824	1.134292	0.283184	1.881742	1.736855	0.001177
825	0.315249	0.510017	1.762681	0.049896	0.000453
826	1.631074	0.871175	0.943183	0.258491	0.155483
827	2.883799	2.254955	0.945766	1.824799	0.016086
828	3.917454	3.487461	6.45055	1.312847	5.73E-12
829	4.30747	3.079395	1.738357	3.482788	0.424436
830	1.835052	0.71177	3.728072	0.096601	0.023424
831	4.622631	3.010844	0.898787	1.696218	0.006815
832	4.595476	3.707243	6.118888	1.826327	0.02714
833	1.314584	0.402523	4.889671	7.192289	4.71E-05
834	1.755841	1.152849	0.621364	0.597225	0.000125
835	2.276722	0.768559	3.065509	2.660467	8.39E-09
836	2.397962	0.88806	2.509923	0.420373	1.51E-05
837	3.279028	2.51897	1.903969	1.398504	0.156318
838	5.962331	4.215686	1.520253	2.707335	1.26E-07
839	4.278605	3.792345	3.087325	1.019461	0.216353
840	2.233176	0.910323	3.461026	1.174806	8.15E-06
841	3.394281	2.481577	7.192995	0.684753	0.021144
842	4.219956	3.155514	2.122433	5.48279	0.468982

843	1.172977	0.354401	0.800972	2.740361	0.139258
844	0.40606	0.152176	0.81734	2.111736	5.89E-05
845	3.49555	2.698479	0.468941	1.700724	1.647528
846	2.718067	1.773643	0.155442	1.838075	0.021433
847	3.328708	2.970375	1.04392	0.295839	1.38E-11
848	1.923744	1.098849	1.544807	2.557106	0.176669
849	5.420076	4.323579	4.141213	0.138859	0.001664
850	2.048388	0.640455	0.774848	2.996489	0.031824
851	1.725857	0.688604	1.073994	1.657654	1.11698
852	1.948209	1.274151	6.41939	0.995649	0.001904
853	1.339457	0.265033	6.598303	2.172836	0.021283
854	2.037545	0.555128	1.210249	0.74561	0.408848
855	1.9102	1.35937	1.388262	0.035126	0.002393
856	2.366916	1.178981	0.113211	1.971199	0.284226
857	2.481202	1.086418	0.798349	0.747372	0.031728
858	3.577039	2.362078	3.070819	0.622902	0.056926
859	1.21935	0.204042	8.674802	0.028448	0.005716
860	5.663131	4.530603	2.141482	1.803445	0.177473
861	1.656786	0.831947	3.954879	0.157186	0.006515
862	1.802058	0.381706	6.123666	1.523987	2.47E-05
863	1.147844	0.346286	0.546495	3.273069	5.34E-05
864	3.224872	1.693132	0.610243	0.873995	0.205915
865	4.18101	2.25726	8.664841	0.273599	1.695382
866	1.581058	0.846524	3.237387	1.978829	1.31E-06
867	0.331676	0.297707	1.344112	0.320901	1.772903
868	4.117913	3.086983	0.937866	9.364445	1.273545
869	1.499563	0.55567	0.614977	0.161907	0.108854
870	1.745766	0.941214	4.000409	0.574857	0.003726
871	2.31017	2.062212	2.685789	1.746722	1.37E-05
872	1.93632	0.966707	1.170715	1.881151	0.00959
873	2.679479	1.510572	26.79131	0.220177	0.000704
874	4.355537	2.902329	3.113722	11.85153	0.306587

875	1.957074	0.940082	5.415386	1.570418	0.006433
876	2.081143	1.142416	2.942658	0.91677	0.001394
877	4.048197	3.368428	2.325755	0.593064	0.000374
878	3.755471	2.727721	2.212998	2.047407	0.014414
879	1.150549	0.777973	2.150919	2.582985	0.028416
880	2.75227	2.14303	2.243995	0.391692	0.013799
881	3.282112	2.524141	1.482768	3.629437	0.036254
882	2.291072	1.488597	2.167987	5.431864	0.111263
883	3.55294	3.246365	0.854953	4.453219	0.045255
884	2.088745	1.193663	1.117247	0.53733	0.003148
885	4.200268	2.909138	1.754298	3.387686	2.449572
886	3.346021	1.920531	5.833285	0.769644	0.004567
887	4.274856	2.847253	4.39202	0.523889	5.08E-11
888	1.692468	0.93724	6.665551	0.570518	0.613326
889	1.571277	0.633351	10.07021	2.921442	0.012761
890	2.984447	1.672678	5.281621	3.839467	0.872108
891	3.829327	2.594471	0.549784	0.034458	0.023056
892	1.772681	0.553333	5.093808	3.201902	1.38E-05
893	3.501906	2.704158	2.77109	1.894951	0.362065
894	1.25258	0.525371	7.0891	5.476204	0.017334
895	3.843251	2.896674	5.510227	2.988024	0.206329
896	4.711966	3.188566	1.78082	0.619016	0.512104
897	2.977678	1.611628	2.550774	2.333604	0.2168
898	1.613806	1.123151	4.136764	0.518922	7.33E-16
899	3.012304	1.32844	2.097971	0.295244	0.250749
900	0.778439	0.666337	0.384243	5.835578	0.006174
901	1.204305	0.277863	4.643569	6.727489	0.002653
902	1.87522	0.567133	7.917999	1.402072	0.089791
903	1.395443	0.614973	0.536898	2.849583	4.307427
904	1.918172	0.636594	0.658431	1.724387	0.065015
905	2.045172	1.215915	7.171502	2.253452	0.00421

906	2.141194	0.995419	4.902986	0.084846	0.087918
907	2.413935	0.854454	7.000789	2.842124	0.101662
908	3.443997	2.481078	5.978455	3.029586	0.416575
909	0.70287	0.366375	7.953874	0.155487	0.001383
910	1.134068	0.384596	2.601854	5.368268	0.082525
911	2.132175	1.174031	0.390439	0.670887	0.001588
912	2.480493	1.027226	1.093264	0.143522	0.031335
913	2.033261	1.174512	1.915277	5.1086	0.456601
914	2.843479	1.530389	0.071543	2.157903	0.010871
915	3.826588	2.368465	1.249368	3.071933	0.000195
916	3.66054	2.467412	3.055175	0.93175	0.007752
917	3.335337	2.741096	2.709735	3.185621	0.623339
918	1.891018	0.982178	1.666953	0.125961	0.076566
919	1.142553	0.285127	1.90287	1.835725	0.07569
920	1.942341	0.624563	3.973669	4.50758	2.45E-07
921	1.056837	0.24293	1.571398	1.666736	0.044094
922	3.110589	2.123024	5.028603	0.742207	0.004427
923	3.047991	2.198777	1.692313	1.540595	0.592955
924	4.972383	4.415276	1.695319	0.871679	0.002712
925	1.800082	1.035327	3.460939	6.62531	0.348427
926	5.420873	3.961534	4.482205	3.361899	1.205608
927	1.65556	1.309878	1.471099	0.520071	1.76E-05
928	1.759524	0.993482	3.611997	0.14369	5.70E-05
929	2.551461	1.773664	2.390935	0.471806	2.93E-07
930	1.239001	0.259096	1.053159	0.37811	3.66E-05
931	2.817799	2.059938	0.496136	1.04307	0.002209
932	2.113276	0.669863	1.690151	3.502627	0.040406
933	4.323321	3.263398	2.591494	2.759643	0.106204
934	2.215284	1.497815	1.122239	2.225682	1.84E-05
935	3.499653	2.032914	2.982592	0.622182	0.160036
936	3.986595	2.981499	0.327708	0.729474	0.006607

937	1.850241	1.053585	3.993165	0.510964	0.621897
938	1.856598	0.661326	0.831954	4.953478	0.026588
939	2.33002	1.177093	0.642286	2.394829	0.02964
940	1.303256	0.19837	4.547915	0.379232	4.74E-05
941	3.826615	2.601126	4.623549	8.012143	0.157195
942	0.961254	0.634646	3.757074	0.464226	0.964807
943	4.765174	3.771482	10.10851	0.107232	6.28E-10
944	1.567502	0.85223	3.245837	1.587794	2.66E-05
945	2.321208	1.955406	8.043373	0.515251	0.689837
946	1.381424	0.320989	2.295656	0.194954	0.017744
947	1.347111	0.70254	0.285913	1.078429	0.028453
948	1.656915	0.893116	0.563569	0.931911	4.86E-05
949	2.153246	1.430794	5.599315	0.430401	0.280489
950	4.226243	3.402936	3.392136	1.856201	0.032669
951	2.646669	1.637029	1.62824	6.348688	0.274163
952	1.424471	0.410943	1.813085	1.947526	0.000537
953	4.973898	3.619044	1.877957	10.06525	5.75E-07
954	1.854953	0.966362	5.410161	2.722431	0.02387
955	2.274488	1.496213	6.177386	3.256414	0.000449
956	1.828027	1.192038	1.688897	0.074148	0.018781
957	1.96767	1.156526	1.305645	4.170161	0.01646
958	1.887798	0.565792	11.95613	0.595585	0.001563
959	1.254279	0.606426	1.918869	1.72886	0.093586
960	1.637336	1.087212	6.83782	0.965782	0.310212
961	2.532683	1.511096	0.021446	1.073759	1.45E-05
962	2.23431	1.129154	3.127772	0.400363	0.247855
963	1.343281	0.236257	4.284772	0.166036	1.76E-06
964	2.788786	2.087756	1.183838	1.241196	0.798357
965	2.077517	1.149313	0.525338	2.779322	6.90E-05
966	1.49265	0.079377	3.077366	0.346053	0.002789
967	1.523696	0.460251	0.088893	0.855515	0.661747

968	2.048772	0.832127	4.257977	3.782158	0.383936
969	2.588392	1.597467	4.779373	2.318085	0.00018
970	1.497149	0.23682	3.201473	1.469293	0.003876
971	4.386847	4.140668	1.505698	0.330805	2.10E-10
972	1.421988	0.987779	3.504467	0.076053	0.015367
973	1.552287	0.678204	1.397441	0.192651	1.12E-10
974	1.191103	0.413863	0.573619	9.325585	2.822187
975	2.259247	0.654472	8.774406	5.392007	0.001515
976	1.235145	0.410758	3.941328	2.300579	0.673819
977	2.841349	2.013997	1.777075	0.631154	0.071676
978	4.092412	3.331586	4.258066	0.715333	4.39E-12
979	2.708007	1.849376	1.910537	0.236486	0.001059
980	3.989453	2.673831	0.06129	1.795664	0.328885
981	0.06818	0.142299	7.891145	0.842915	6.44E-05
982	2.104885	1.315552	1.062857	1.782533	0.006676
983	1.957296	1.137551	1.480249	1.192374	0.002014
984	1.5147	1.035231	1.746596	1.991946	0.771544
985	6.371305	5.11903	1.697849	0.309662	2.873443
986	1.048196	0.027043	11.34407	2.482934	0.005288
987	3.652963	3.129786	0.333785	1.9251	0.000108
988	2.246701	1.317499	0.629446	0.139692	1.029964
989	3.994179	2.759838	3.671262	6.751256	0.061968
990	1.589092	0.477279	2.166715	1.091551	0.000138
991	4.222025	3.003245	3.519251	3.500716	0.000197
992	1.265352	0.569472	4.595451	6.017573	0.033469
993	1.065474	0.175375	1.651074	3.80001	0.000245
994	1.465737	0.475848	3.195066	0.056581	0.016677
995	2.12062	1.174444	1.771632	3.691944	3.39E-11
996	3.692855	2.676138	5.395173	0.021225	0.14248
997	2.214392	1.01704	1.175612	3.889839	0.007755
998	4.101087	2.919852	1.174059	0.827693	0.593005
999	3.54205	2.173215	0.563419	0.765204	0.019542

1000	1.48314	0.449084	3.93685	3.095491	0.001698
1001	1.515844	0.750757	4.128892	3.215931	0.032788
1002	2.725257	1.911314	1.541996	1.270083	0.006182
1003	1.512844	0.166287	1.875553	0.152184	0.784349
1004	4.016159	2.772473	10.61605	2.568304	0.358929
1005	2.504494	2.61594	2.282747	1.496359	3.93E-05
1006	3.107581	2.269641	0.069433	2.651908	5.56E-05
1007	2.140358	1.062207	1.067177	0.603331	0.107063
1008	2.163324	0.938138	1.172969	0.334658	2.67E-05
1009	5.106883	3.989573	4.764475	7.41914	0.000167
1010	3.160547	2.103538	1.095422	0.386791	0.011147
1011	3.407717	1.443042	0.758986	0.79976	3.06E-07
1012	3.078834	2.760574	13.26213	0.748697	0.260414
1013	2.156359	1.554604	4.906581	3.486909	0.009612
1014	2.025122	1.139349	1.477383	1.201682	1.908368
1015	3.687418	3.057216	2.289073	1.710719	0.009593
1016	1.058996	0.745483	3.088334	0.961362	0.015241
1017	2.031677	1.432782	5.609138	4.960362	0.00052
1018	1.77734	0.691698	3.932297	0.890732	2.60945
1019	1.585648	0.338649	1.984952	2.270104	0.001582
1020	1.821563	1.792175	0.471107	2.706751	0.009399
1021	2.997328	2.509766	1.496248	2.454334	0.077579
1022	2.869199	1.785455	2.758613	1.057863	0.200149
1023	2.493367	1.538807	1.785756	1.649943	0.825699
1024	1.223988	0.742245	3.211037	1.429574	2.17E-11
1025	3.835765	2.310658	3.779813	6.524638	0.124469
1026	2.421652	1.997337	6.328987	0.117792	0.524582
1027	1.588848	0.655803	4.315815	1.570436	0.22243
1028	2.099357	1.413408	3.905065	3.358481	3.79E-06
1029	7.912084	7.096583	2.968988	3.143622	2.85E-05
1030	0.212825	0.393291	4.862717	3.472561	0.000741

1031	1.220518	0.603405	7.538287	9.316506	0.001471
1032	3.794993	2.175435	2.771735	3.625933	0.189927
1033	2.26644	0.860871	2.600252	1.380171	0.370055
1034	1.696809	0.869892	1.996117	2.018501	0.038644
1035	1.861311	1.22409	1.769965	0.836074	0.057962
1036	4.1447	3.150876	4.355917	0.576474	1.323358
1037	1.855199	1.252835	3.443582	3.199089	0.173709
1038	4.67982	3.035049	1.129299	1.802693	0.041137
1039	1.825287	0.675989	3.408375	1.334689	0.245987
1040	2.234824	1.498436	2.925514	0.944636	0.001573
1041	2.69362	1.601296	4.287393	0.918471	4.54E-05
1042	1.400931	0.329261	2.081441	0.104014	6.38E-07
1043	1.298205	0.414593	3.941228	2.209741	1.11E-05
1044	2.991546	2.398259	3.171325	2.883909	0.126568
1045	1.424221	0.191485	0.626621	2.141235	1.72E-08

1046	1.524968	0.597835	1.891057	2.536554	0.0083
1047	5.608726	3.713219	4.252275	0.086665	0.30071
1048	2.908209	1.019634	0.084403	0.888731	0.009561
1049	1.126118	0.334456	7.335929	1.080336	0.196013
1050	2.141086	0.737422	0.332805	2.520128	4.81E-10
1051	2.703392	0.750564	0.07653	1.72003	0.016632
1052	1.609283	0.326243	3.721155	0.423512	0.099259
1053	3.127214	2.148122	4.156736	0.293812	0.007142
1054	1.301373	0.990863	0.232152	0.908057	0.289077
1055	2.458091	1.07541	2.859132	0.255316	0.524344
1056	3.249434	1.23348	5.819687	1.711571	1.872692
1057	1.906717	0.810172	4.437976	0.151177	0.014275
1058	1.872829	1.455877	2.533916	1.126885	0.032346
1059	1.776846	0.730126	0.439866	7.739211	0.105057
1060	0.771929	0.069228	0.796116	4.845663	0.857354
1061	2.065546	1.719859	4.256501	0.588076	0.746748

1062	1.402919	0.042713	2.063996	1.32517	2.13E-08
1063	1.968963	1.058192	3.469458	1.805311	1.41E-10
1064	2.231742	0.47447	8.566457	1.104671	0.002594
1065	1.485738	0.463159	7.862933	0.292969	2.93E-09
1066	4.398011	3.511905	4.907967	1.111848	0.000283
1067	3.402687	2.758275	7.560431	3.508656	0.034797
1068	2.998037	1.24103	5.570735	3.457277	7.11E-08
1069	1.850202	1.298205	2.002336	2.257872	0.436158
1070	1.250954	0.170634	2.864635	2.823082	0.001314
1071	1.914652	0.279883	0.520617	4.743063	0.003011
1072	4.612154	3.474913	1.20429	3.229754	0.21987
1073	2.498334	1.455003	1.106457	0.40598	0.472914
1074	2.462056	1.635561	5.378544	0.687226	0.031579
1075	1.941365	0.65838	1.112047	0.753574	0.000276
1076	2.313618	0.733491	7.407123	8.720599	0.109094
1077	2.942295	2.192155	0.155616	3.247612	1.11E-05
1078	3.572269	2.594333	3.073563	1.312329	0.000179
1079	3.133457	2.256912	1.912618	1.530665	0.114217
1080	0.757737	0.223714	2.690604	1.715467	0.000322
1081	3.273225	2.570687	1.838346	1.011441	0.173545
1082	2.170218	0.835368	5.184392	2.380088	7.71E-08
1083	1.971682	1.291673	5.384882	2.812483	0.000186
1084	1.946694	0.512991	3.063179	0.737942	0.025897
1085	2.16719	1.217068	1.068192	1.305469	2.76E-12
1086	2.270611	1.104762	1.793396	1.106517	0.012609
1087	2.305946	1.618154	1.875121	0.647966	0.942993
1088	2.40842	0.940861	1.39744	0.557004	0.150941
1089	2.969192	1.921433	6.39156	0.404638	1.133496
1090	1.295332	0.349214	6.047307	0.89592	0.199844
1091	1.223722	0.315296	0.584682	0.649093	4.53E-05
1092	5.237713	4.016498	11.8794	5.874956	1.04E-06

1093	2.496577	1.616743	3.31152	0.446182	0.111739
1094	4.330211	3.529554	3.570163	4.315489	0.01567
1095	1.966416	0.914084	0.049086	0.44068	0.018668
1096	3.574955	2.421853	3.948887	0.78845	0.004272
1097	1.039323	0.439647	3.105068	0.828224	0.01562
1098	0.773285	0.26084	1.730607	0.972012	5.18E-06
1099	2.360296	1.83275	2.230967	3.228589	0.761694
1100	1.285067	0.457869	2.426828	3.177385	0.351896
1101	3.095759	2.357525	0.80177	5.390536	0.114938
1102	1.512196	0.819631	3.715028	2.515632	0.039625
1103	4.233189	3.280858	0.360053	0.147306	0.003295
1104	3.215891	2.666271	1.173576	0.120365	0.003399
1105	1.556422	0.483293	0.74685	2.128064	4.35E-06
1106	2.201743	1.742011	1.100055	4.071538	1.154609
1107	2.015378	1.740321	4.992648	1.395663	0.015151
1108	5.285897	2.98422	1.201926	0.540429	0.0017
1109	1.507514	1.038845	1.142614	8.239093	0.289519
1110	1.902697	1.149439	0.652182	1.546505	0.0034
1111	2.588838	1.16128	3.341716	2.631533	0.224992
1112	1.89627	1.341653	1.668458	0.304681	0.234758
1113	2.317517	1.24602	8.198309	3.059499	0.009133
1114	1.557577	1.225908	2.766749	3.516259	0.280862
1115	1.50918	0.991138	0.376469	1.697	0.021869
1116	2.948384	2.272081	2.827257	4.49004	0.314406
1117	2.227181	0.50249	12.3025	1.014394	0.000681
1118	1.70887	1.15486	0.6172	0.972799	0.085048
1119	0.898997	0.446042	1.199157	5.574217	0.001815
1120	1.330762	1.305762	2.104779	1.954896	0.002802
1121	1.766288	1.451197	5.094272	4.33236	2.990307
1122	1.096723	0.134855	1.788255	0.308236	0.23093
1123	1.470184	0.416461	1.765759	2.686152	0.048293
1124	1.827444	0.225979	7.631905	2.335281	0.011845

1125	2.409479	1.625345	0.370199	0.927325	0.00374
1126	0.661646	0.088721	4.497164	0.35332	4.12E-06
1127	1.760557	0.706526	6.079359	1.559678	0.10636
1128	1.703723	1.203699	4.529985	1.286345	0.76786
1129	3.029961	1.781258	3.037501	4.061762	5.27E-09
1130	1.62085	0.502812	2.7312	0.160327	4.16E-05
1131	1.419844	0.44753	8.05197	1.677943	0.946247
1132	1.758069	0.829638	3.995429	4.145657	0.000473
1133	2.077519	1.361987	2.9058	1.954639	0.016227
1134	2.430888	1.476577	8.18176	8.182283	0.785382
1135	2.648263	1.356302	2.240845	3.924083	3.59E-06
1136	1.965376	0.739679	4.502066	0.011819	0.000253
1137	2.275712	0.675554	0.163323	0.216014	0.021293
1138	2.091493	0.626266	3.532572	0.141693	0.012316
1139	2.372296	1.085451	1.359977	7.865883	2.40E-06
1140	1.843733	1.263453	1.767646	0.783452	0.591089
1141	1.052863	0.367003	6.343036	0.183938	0.602554
1142	1.765145	1.376033	2.511295	0.552828	0.000982
1143	2.039018	0.60742	2.212672	1.781912	0.002843
1144	2.5587	0.473746	2.064508	0.119677	0.000322
1145	2.733422	1.441791	4.412629	2.739437	5.34E-05
1146	1.120956	0.345168	0.228897	0.719127	0.001452
1147	6.296642	5.356163	1.869628	0.197479	0.001731
1148	2.890093	1.999412	1.337457	0.068678	0.325511
1149	1.263058	0.618784	4.210809	4.487066	0.008693
1150	1.31957	0.594141	2.100011	2.904626	0.075603
1151	2.441966	0.57939	1.925171	1.553493	0.276765
1152	2.968636	1.909456	0.839403	1.586271	0.020727
1153	0.932288	0.465354	3.24431	0.565446	0.352306
1154	1.666364	1.056195	0.91693	0.708465	0.727546
1155	2.482616	1.619941	0.735289	0.583238	0.139089

1156	3.078312	1.830086	2.163948	0.052978	0.061985
1157	1.405431	0.363846	6.476049	6.689709	0.001173
1158	0.96042	0.26574	6.861188	0.151572	0.778319
1159	3.321812	2.173317	7.800495	0.97502	0.053379
1160	3.749056	1.97767	1.841889	2.834553	0.463417
1161	1.750079	1.064208	2.701845	0.059887	0.226678
1162	2.157968	0.802538	0.472089	3.384296	2.64E-05
1163	1.776055	0.663584	2.20895	3.453649	1.249599
1164	5.123032	3.984452	3.05383	1.087099	0.002161
1165	2.036939	0.906619	2.242411	0.611921	0.003087
1166	2.204536	0.264025	5.801536	8.928449	0.282072
1167	2.693042	2.079928	2.219153	1.180751	0.421467
1168	3.197769	2.462905	0.68522	0.606375	0.000637
1169	2.042209	0.907392	1.725375	0.924303	0.002728
1170	2.07174	1.276176	2.588333	1.340111	0.000157
1171	4.067887	3.090122	1.0763	1.778598	0.020273
1172	2.149403	1.602032	0.408624	0.060833	2.74E-08
1173	2.343736	1.120579	6.631268	1.022413	0.013929
1174	1.328544	0.527463	8.132269	0.531803	4.64E-07
1175	1.634043	1.011952	1.822161	0.664293	4.89E-07
1176	1.27873	0.470975	0.675912	0.41654	3.11E-08
1177	1.284113	0.236263	4.425873	0.114164	0.364681
1178	2.810391	2.136468	2.940995	1.508922	0.048279
1179	1.59157	0.661495	1.002733	0.363769	0.04607
1180	3.895558	2.375978	0.565234	0.169799	9.69E-05
1181	2.13601	0.977938	2.087782	2.475445	1.10E-07
1182	3.090829	1.970292	0.653001	5.421299	0.041064
1183	3.591491	2.438816	1.166668	3.748284	0.009077
1184	1.968643	1.111725	1.313435	1.383889	0.006294
1185	1.145635	0.330695	9.53752	6.265918	0.007376
1186	3.394557	2.80149	3.213062	1.797558	0.00111

1187	2.277393	2.104463	10.18964	1.159226	0.013118
1188	3.047088	1.053305	0.184552	1.482938	6.21E-06
1189	5.990718	5.493191	2.712236	0.438307	7.64E-07
1190	1.221393	0.029507	1.723323	2.400363	0.915897
1191	2.387777	0.465046	0.970406	0.218701	0.000114
1192	1.258326	0.106499	0.713469	2.236116	0.065563
1193	3.763572	2.919338	3.130906	3.3413	1.130466
1194	1.982217	1.257273	2.154879	2.225443	0.056334
1195	0.690274	0.241601	1.724312	0.715308	2.02E-05
1196	3.457931	2.713234	6.768725	6.220022	0.000163
1197	0.832087	0.079753	2.032088	1.019831	3.03E-05
1198	2.868507	1.988398	1.914954	0.249162	0.004011
1199	2.495943	1.540616	3.598186	4.193369	0.001291
1200	2.076055	1.052299	2.472017	1.366326	0.399381
1201	2.185803	0.870075	2.007441	3.057609	0.268047
1202	5.131785	3.235122	2.216457	5.222829	0.011969
1203	4.585092	3.729978	4.411891	0.257961	7.94E-08
1204	3.496134	1.477054	0.655002	2.649447	0.003916
1205	2.369227	1.220486	4.463957	3.16158	0.063765
1206	2.704253	2.21255	3.209614	0.552247	0.145516
1207	3.952012	2.781136	4.217943	2.940777	0.027391
1208	3.943374	2.535139	1.282853	1.025802	0.00012
1209	1.74841	1.034765	1.917344	0.003208	0.079538
1210	1.436575	0.648879	3.159382	1.086687	0.013899
1211	1.375252	0.750033	10.97418	4.877003	1.88E-07
1212	1.98764	1.141115	0.597964	0.567683	0.284192
1213	2.149385	1.708834	0.510065	4.02046	0.081801
1214	2.432331	1.269753	1.069506	2.707993	0.000671
1215	4.033947	3.075896	5.565841	2.22161	0.012492
1216	1.473625	0.919253	1.606776	1.466137	0.835294
1217	4.771912	3.759345	6.95514	2.295185	4.31E-08

1218	3.983916	2.288785	1.63065	0.21453	0.153406
1219	4.525398	3.938657	2.78154	3.6112	0.000993
1220	5.179882	4.662593	0.506794	0.242515	0.000388
1221	1.337573	0.59409	1.801218	4.240399	2.505934
1222	1.343683	0.860431	0.115727	4.625082	0.00086
1223	2.804168	1.875267	4.21464	2.066705	0.685414
1224	1.488063	0.922164	5.800611	0.12377	0.002986
1225	1.664702	0.776501	4.248013	0.715534	0.004034
1226	1.589579	1.044586	3.247231	2.464636	0.002747
1227	3.390328	2.607585	4.672052	2.051473	0.009392
1228	1.959513	1.456613	2.470409	0.40532	0.548479
1229	2.222551	1.128705	5.525934	3.031519	0.051534
1230	2.737902	1.758509	3.345577	1.497164	0.344574
1231	5.409507	4.446478	2.594173	0.375613	0.002776
1232	0.645113	0.446617	0.020302	4.807766	0.03623
1233	2.498429	1.134262	4.037759	3.279682	6.61E-07
1234	1.348919	0.372992	1.455923	0.024752	3.52E-09
1235	2.859558	1.201924	2.021775	9.287628	0.264228
1236	1.994376	0.517641	0.143504	0.110133	0.118863
1237	1.358966	0.321229	3.116046	0.197479	6.86E-05
1238	2.491229	1.353935	1.972928	0.348382	0.006016
1239	3.495233	2.940021	1.467891	3.011264	1.25968
1240	1.968947	1.117423	2.424743	2.225053	9.93E-05
1241	2.730287	2.140335	1.767795	2.55049	0.677546
1242	1.587324	0.76672	2.771621	0.292179	0.51877
1243	3.431575	2.190496	1.678652	5.671937	3.25E-08
1244	0.833777	0.657425	0.327154	0.806476	1.73E-05
1245	1.545152	0.184285	0.886625	2.907344	0.006127
1246	1.427135	0.839481	1.185271	3.469236	0.010539
1247	3.873641	2.512609	3.691702	2.613365	0.084665
1248	2.235615	1.328824	1.32003	2.05056	2.020265
1249	2.86754	1.859833	0.068079	4.146416	0.000371

1250	1.485749	0.938243	8.389897	1.110421	0.017336
1251	1.36116	0.590531	1.423653	0.887304	0.006167
1252	1.909988	0.88063	7.403195	0.81889	1.263099
1253	1.28945	0.349613	2.597854	3.468703	0.081072
1254	0.781854	0.27922	1.278036	3.358801	0.001347
1255	1.780969	0.185483	1.692851	0.168659	0.172127
1256	1.64828	0.139651	1.265584	1.754439	0.002232
1257	1.705525	0.773535	6.867996	6.341075	0.003541
1258	4.5386	3.809271	0.378289	3.130457	0.512517
1259	2.634724	1.008021	3.944271	0.173137	0.000271
1260	1.341258	1.074333	3.566504	2.094951	0.047894
1261	0.953309	0.360273	3.699349	2.902742	0.001414
1262	1.520226	1.102235	3.489044	0.788116	0.006453
1263	1.798224	1.336699	5.029831	0.102208	0.008217
1264	2.198088	1.245574	4.094984	0.849457	0.470126
1265	3.238193	1.898791	1.292137	1.433972	0.048986
1266	1.186471	0.362679	0.958396	1.619512	0.012087
1267	3.441054	2.505532	6.422197	3.681275	7.53E-07
1268	2.301256	1.369177	0.286467	1.099758	0.00015
1269	3.616019	2.701995	0.407244	0.134944	0.001407
1270	0.866292	0.503241	2.690873	1.440545	0.001825
1271	3.376124	2.113964	4.479815	0.497029	0.044019
1272	2.946946	2.342742	0.830488	0.391785	7.88E-05
1273	1.787292	1.331296	1.60376	0.476205	0.001824
1274	2.124668	0.841144	0.755564	0.105082	0.032925
1275	2.435195	1.41084	3.002082	0.996089	0.009863
1276	2.421712	1.598569	6.104505	0.572571	0.926553
1277	3.752066	2.891991	1.941027	0.526108	0.051872
1278	1.616494	0.853863	5.111113	3.508288	7.03E-13
1279	0.925318	0.190252	2.335936	0.29983	1.07E-06
1280	3.47906	1.981721	0.671082	2.188243	0.062133

1281	4.793959	2.557873	1.549991	0.847567	0.000295
1282	1.363191	0.541725	3.349376	5.020643	9.74E-07
1283	2.920566	1.577102	4.71674	0.434931	0.320955
1284	2.3498	1.133029	3.632341	1.64034	0.349365
1285	3.806191	1.700217	0.604073	0.062416	0.08311
1286	1.198581	0.505112	5.182108	2.696303	0.317849
1287	3.040985	1.6667	2.326183	0.963841	0.164043
1288	1.407192	0.229225	7.893236	3.134366	0.159916
1289	1.557965	0.649535	6.139842	1.502908	0.169268
1290	5.761825	4.901214	5.070462	7.013682	5.46E-07
1291	2.743345	0.743845	2.632889	4.335009	0.352939
1292	2.222326	0.764763	6.948438	1.051693	0.05352
1293	3.424444	2.87197	0.771851	5.874282	1.43E-05
1294	3.908303	2.954172	0.666822	2.354476	4.23E-05
1295	2.640775	1.511396	1.579557	2.471403	0.563242
1296	0.971774	0.343925	5.20332	0.261292	0.053055
1297	2.844564	1.170671	0.835884	2.648927	2.31E-05
1298	5.998708	4.58985	4.988753	2.512475	0.001177
1299	2.374045	1.32351	1.066225	0.192712	1.17E-07
1300	2.638349	1.643159	3.898611	0.598501	0.000562
1301	2.059043	0.971793	1.117235	1.629774	0.509008
1302	1.546694	0.40147	0.941578	2.37276	0.011806
1303	2.482658	1.705609	2.177154	0.286923	2.99E-08
1304	2.545957	1.407442	3.731995	1.28498	0.008927
1305	2.939379	1.877979	1.837064	1.179232	3.17E-05
1306	1.360671	0.703723	1.072506	0.186077	1.56E-07
1307	1.093641	0.865431	6.852588	0.411116	0.122184
1308	3.992207	3.26004	1.700842	2.874812	5.35E-08
1309	2.754435	1.560909	3.788193	2.048217	8.24E-06
1310	1.426797	0.83783	1.020538	1.009815	0.432045
1311	1.665821	0.64639	10.62124	2.061417	0.013605

1312	2.366887	1.066057	1.009717	0.568077	1.12E-05
1313	1.884955	0.440922	6.087438	1.419579	0.006119
1314	0.792389	0.126459	2.702334	7.094041	0.021265
1315	2.965102	1.927353	10.5208	0.125879	4.95E-05
1316	5.225172	4.619925	5.261802	2.543079	0.262504
1317	1.781175	1.073136	5.05109	1.211598	0.012133
1318	2.334816	0.881409	0.608845	2.2911	0.091479
1319	3.205961	1.844432	6.115811	2.045588	0.001962
1320	2.063374	1.079615	1.510348	4.509356	0.001386
1321	2.086486	0.852584	1.345368	0.43507	0.000961
1322	0.916946	0.673433	1.008695	1.922625	0.222997
1323	1.354439	0.56837	3.897999	0.881586	0.294764
1324	1.419406	0.658643	3.049748	0.117912	0.040245
1325	5.573353	4.846553	1.902602	0.575569	0.081469
1326	-0.23741	0.082695	0.922546	0.4634	5.27E-08
1327	1.77776	0.165707	0.51179	0.038768	8.43E-05
1328	1.309645	0.187487	1.894337	1.646191	2.866143
1329	1.780575	0.958965	3.436545	5.786109	3.57E-06
1330	0.921023	0.459546	1.504344	2.853109	0.023142
1331	2.502605	1.115148	1.957592	1.161264	0.138788
1332	1.281736	0.273226	4.049423	1.46687	0.003054
1333	1.000494	0.734209	7.400027	2.3347	0.00299
1334	2.235036	0.935875	11.93977	0.761576	0.282084
1335	3.477017	2.266229	1.078963	2.409527	0.005264
1336	3.857193	3.208016	1.054319	3.757998	0.023706
1337	2.23396	1.239453	0.994865	2.955664	0.041017
1338	1.861444	0.782796	0.814227	9.189051	0.689714
1339	2.351969	1.706308	4.072776	0.685365	0.028463
1340	2.327771	0.773168	4.200427	0.652145	8.40E-05
1341	1.486306	0.458254	0.114949	1.425336	0.087553
1342	1.515816	0.611016	5.907365	2.066219	2.229058

1343	2.980033	2.375632	2.31884	0.111505	0.734054
1344	2.963582	1.09134	2.490104	0.499846	0.291182
1345	3.088376	2.107298	0.988489	1.565121	0.232305
1346	2.321267	1.476137	3.559059	0.698157	0.034168
1347	2.736277	1.477491	1.44712	0.422652	0.000403
1348	1.892421	0.617569	0.374733	7.502355	0.097789
1349	1.222126	0.449034	2.688562	0.078364	0.018099
1350	4.613796	3.722506	0.299833	0.462193	4.33E-11
1351	1.938233	0.658299	1.900899	2.706469	0.756748
1352	1.979531	0.805927	3.385678	2.628027	1.17E-07
1353	1.449658	0.806155	0.480415	5.865253	2.05E-08
1354	2.250708	1.550039	0.744105	4.369048	0.000862
1355	4.046798	2.457088	1.128573	1.422869	0.01351
1356	1.907836	1.568995	1.752727	1.786454	0.000387
1357	5.037174	3.468657	1.984213	1.815729	0.081876
1358	2.532942	2.337453	3.470066	0.338756	0.186491
1359	1.6387	0.499463	4.005455	2.073082	0.008852
1360	1.965768	0.219169	4.110287	5.553186	0.164723
1361	3.210469	1.800567	0.432119	0.070784	0.003305
1362	1.250219	0.473229	0.310794	0.845635	0.014969
1363	1.34094	0.045213	2.964779	2.64924	2.947918
1364	1.647976	0.7353	0.381934	2.401359	0.003955
1365	1.615329	0.476848	5.755801	2.625525	0.244553
1366	2.062971	0.842638	8.69078	2.948736	0.919854
1367	1.522074	0.29072	2.608508	2.435081	0.000755
1368	5.619452	4.098418	1.968335	0.834117	0.117638
1369	3.543873	2.632727	5.686049	6.406512	0.606787
1370	0.830215	0.110594	3.142041	0.919388	0.156286
1371	1.965539	1.353869	4.503221	0.382427	0.03701
1372	1.751413	0.424889	1.255948	0.7115	0.000142
1373	2.650477	1.328322	0.538123	0.037275	0.115929

1374	1.251249	0.271322	7.865261	3.268753	0.156861
1375	1.700917	1.139773	0.158207	2.630786	3.21E-08
1376	2.274454	1.369703	4.081815	2.156421	7.33E-08
1377	0.828586	0.459829	0.447294	0.929649	0.065712
1378	2.919443	2.04415	5.461597	2.491828	0.006972
1379	2.30934	1.528301	4.342596	1.308541	1.10E-05
1380	1.406066	0.332037	3.591741	2.406986	0.01103
1381	3.143723	2.103231	8.153136	3.086897	0.199836
1382	1.70548	0.754236	1.958541	0.254427	0.004212
1383	2.835787	2.103087	2.345778	1.825209	5.17E-06
1384	1.83528	0.858512	0.651662	0.592145	0.010475
1385	1.46476	0.451516	6.794334	7.142923	1.016862
1386	2.602157	0.763627	0.63244	2.882473	0.202995
1387	1.820733	1.16752	6.206462	1.419652	0.075207
1388	2.823006	1.567129	2.830192	0.100554	0.010196
1389	2.075189	0.866158	1.599262	1.601768	3.09E-12
1390	2.453109	2.200423	1.82386	1.206197	0.583247
1391	2.072486	0.574211	3.739344	0.948676	0.000738
1392	1.140277	0.743568	0.883924	3.257788	0.007502
1393	3.928653	3.175826	2.577997	0.096843	1.99E-05
1394	6.226133	5.27226	0.460081	0.14398	0.016617
1395	2.621755	1.350989	4.999364	0.805857	0.060918
1396	1.341234	0.250605	0.84544	2.698239	0.000108
1397	2.43096	0.938931	0.367396	4.8179	1.151205
1398	4.988484	4.23841	4.379277	0.960898	0.040035
1399	3.691025	2.968356	0.575509	0.960368	0.218123
1400	3.794281	2.145515	1.123029	2.047817	2.22E-06
1401	1.473531	0.465984	3.294584	1.199341	1.89E-08
1402	4.429997	3.808175	2.596639	0.522612	0.569615
1403	3.652122	1.833438	0.550987	0.530932	1.844119
1404	1.343197	0.136206	3.18289	0.616828	0.051431
1405	1.649293	0.828707	3.033908	3.367467	0.116531

1406	1.606333	0.899063	4.729204	2.232891	4.74E-06
1407	2.52144	1.025529	1.573951	4.770992	0.030226
1408	1.935162	0.896191	0.872022	7.829326	0.024092
1409	3.890193	2.882939	12.19981	1.681763	0.006637
1410	1.263689	0.24778	0.335243	0.463953	0.798139
1411	7.681135	5.78506	3.878697	0.353005	0.000134
1412	2.215712	1.192391	0.785054	8.470985	0.167061
1413	2.032192	0.915432	7.191804	1.426457	1.904564
1414	2.835998	1.656365	4.482501	0.989587	0.00204
1415	1.257244	0.519475	5.078193	3.913889	0.001551
1416	1.514711	0.41167	1.879917	0.053894	1.25E-08
1417	1.341655	0.096553	0.292342	2.500416	0.414279
1418	2.003414	1.575714	4.767234	0.789461	0.08922
1419	3.520983	2.432557	1.445059	3.568472	0.191305
1420	1.787835	1.313048	4.514434	2.752659	0.064672
1421	2.009524	1.11682	3.145804	1.122847	0.037894
1422	6.168892	5.143028	3.744027	1.764873	0.430488
1423	1.485342	0.871259	2.017969	0.269507	7.17E-05
1424	0.973315	0.153361	1.346585	0.519718	0.419999
1425	0.700419	0.098229	0.682241	1.790962	0.01712
1426	3.253539	1.89287	2.595372	1.206365	0.000147
1427	2.956994	1.851932	2.840485	0.756	0.000136
1428	1.730984	1.074927	0.515425	0.377	0.016585
1429	1.647631	0.58485	5.613749	1.531707	0.003496
1430	1.880019	0.963208	2.173012	2.385265	0.002008
1431	5.604	4.638773	2.614635	0.217157	4.10E-09
1432	2.817509	1.739798	0.247109	1.317283	0.038999
1433	2.02046	1.197514	2.769897	3.738831	0.358991
1434	0.610867	0.166923	3.920136	2.043804	2.11E-10
1435	5.337402	4.17266	4.533056	0.443127	0.001773
1436	2.32284	1.122578	2.563209	1.717528	0.13954

1437	2.165639	0.221628	2.998469	0.089476	1.65E-09
1438	2.132394	1.662989	1.377219	5.583429	0.051452
1439	1.500353	0.10953	1.658581	0.765022	0.036858
1440	2.883634	0.876676	2.992289	0.771509	0.004192
1441	2.729825	1.536615	1.699989	2.822122	8.69E-07
1442	2.45892	1.35682	0.425371	0.208598	9.40E-08
1443	1.364563	0.551832	4.676781	0.276151	0.003223
1444	2.755119	1.756378	6.115862	1.701663	0.025592
1445	3.587754	2.526828	1.732068	1.442645	0.206544
1446	2.541184	1.695992	0.696033	0.140891	9.33E-05
1447	1.873697	0.563743	1.007822	5.220632	1.29E-05
1448	2.09549	1.082492	3.683677	0.684454	0.219659
1449	2.222756	1.294494	0.752645	1.037833	0.667451
1450	1.596687	0.368135	5.379943	1.448294	0.270609
1451	1.012977	0.411624	1.395179	2.09524	0.000905
1452	2.750884	1.773007	5.489871	0.412309	1.023326
1453	8.92108	7.579934	1.972454	0.388662	0.036754
1454	4.307771	2.903194	2.165116	0.667935	0.444392
1455	3.379931	1.683277	0.600089	2.161086	0.005378
1456	3.20579	2.007963	0.74018	2.007273	0.858831
1457	1.206785	0.77568	3.724053	0.105895	0.046933
1458	0.999216	0.626417	3.320137	0.270397	0.047241
1459	3.368867	2.036454	1.656132	9.308937	2.61E-06
1460	2.024468	0.811792	2.737646	1.64557	0.600817
1461	2.973192	1.543748	0.615499	1.683339	9.85E-05
1462	2.75612	1.519328	1.168256	6.876904	2.24E-09
1463	1.335245	0.361322	0.363685	0.186863	0.001599
1464	3.285891	1.233189	2.730932	4.263412	0.034374
1465	1.966491	0.549347	1.429703	0.849769	0.027014
1466	2.101284	1.032526	1.81336	4.001853	0.705071
1467	1.530466	0.144425	2.549239	0.865449	0.007324

1468	1.930182	1.36335	0.360388	0.764854	0.198807
1469	3.135871	2.256357	2.567358	7.473715	0.003533
1470	1.611796	0.186856	4.433278	0.948025	0.004198
1471	1.987581	0.882843	3.02089	1.312463	0.063609
1472	1.860293	0.703935	0.787555	3.735711	1.21E-05
1473	1.215519	0.255743	3.832589	0.182495	0.069146
1474	3.72903	1.973429	7.996841	0.048269	0.351448
1475	2.042543	1.187289	1.294302	0.279923	0.001725
1476	2.841146	2.389004	0.299029	1.852556	0.020391
1477	2.055085	1.445284	0.826826	3.940517	0.039038
1478	5.213566	4.411639	2.49814	0.096661	0.007344
1479	1.422187	0.535181	3.909143	0.692032	0.000703
1480	1.821026	0.692674	1.693496	3.376988	1.27341
1481	1.741973	1.236723	3.387096	0.977788	0.04402
1482	4.021012	3.095704	3.419033	0.545749	0.000233
1483	1.72675	1.301391	4.968847	1.781806	0.178803
1484	2.462597	1.528727	0.344852	0.109756	0.000583
1485	2.055894	1.369062	3.864708	0.58748	0.055269
1486	4.482386	3.457381	9.685957	0.585725	0.018562
1487	3.368479	1.823582	5.259758	1.641739	2.39E-06
1488	1.671087	0.996434	6.160087	0.87438	0.003892
1489	1.304558	0.443987	1.354913	0.807267	1.057389
1490	3.209982	2.278749	2.665669	2.111681	0.15986
1491	1.078596	0.407082	0.366441	1.991518	0.230272
1492	1.612227	0.568093	1.061247	2.826953	0.029604
1493	1.348252	0.371887	2.916333	8.585608	0.006001
1494	4.670891	4.037593	1.421633	0.082565	0.063789
1495	1.737021	0.709824	1.967262	0.334996	1.69E-06
1496	2.217022	0.535231	0.36734	3.106706	1.276007
1497	2.985699	2.014341	2.049663	1.509754	1.37E-05
1498	2.806784	1.447587	0.271924	0.495131	0.067647

1499	5.110307	3.551745	4.802687	2.521909	0.008685
1500	2.233381	0.911091	8.520062	0.317033	0.198445
1501	1.096595	0.152411	2.268444	0.119862	0.006104
1502	1.891923	0.03329	1.376898	3.189091	0.012439
1503	2.340142	1.087655	0.147118	0.495143	2.226817
1504	2.258744	1.236035	0.596762	3.989766	0.186369
1505	1.90404	0.742089	6.323454	2.269343	0.005172
1506	1.298015	0.128045	0.959525	4.242672	2.483491
1507	2.540206	1.396877	1.007711	1.553718	0.101076
1508	3.538217	3.230288	1.079274	13.03179	0.004076
1509	5.427216	4.606217	1.335191	1.679809	0.042659
1510	0.881271	0.027693	2.666608	0.748838	0.016251
1511	3.21398	2.055713	0.534138	3.499319	0.361813
1512	3.373856	1.915032	4.47107	1.618396	0.215683
1513	1.316371	0.850838	6.067937	4.508103	0.101045
1514	2.605449	2.196431	7.994883	4.210377	0.183891
1515	1.295936	0.373135	1.8762	6.618196	0.322894
1516	1.212608	1.169283	2.187326	1.742035	2.08E-05
1517	1.23947	0.524043	1.313696	1.226066	0.001949
1518	2.897484	1.441308	3.496722	0.275074	0.23173
1519	2.476039	1.170558	1.702311	2.49038	0.497392
1520	5.417092	3.725893	7.136618	0.236127	0.005875
1521	1.258396	0.548093	2.811575	0.215775	1.11E-05
1522	3.103365	2.461335	0.230933	1.127388	7.54E-05
1523	1.241224	0.141527	3.066272	1.583058	6.99E-05
1524	1.642071	0.697334	2.795389	1.814523	0.526666
1525	2.01103	0.629137	3.601394	2.892941	0.384802
1526	5.947182	4.878234	1.021352	0.245036	0.518969
1527	1.53975	0.622868	1.313855	0.808241	0.153508
1528	1.898312	1.091689	0.35755	0.602967	1.36E-07
1529	3.638916	2.883457	0.760197	1.834888	0.069493
1530	2.409734	1.261794	4.59826	3.819297	0.256018

1531	2.507862	1.19177	2.124103	1.618661	0.216755
1532	3.499401	2.238897	8.95707	1.592512	0.000959
1533	1.91782	0.870221	1.671077	1.830997	0.000305
1534	2.506088	1.207049	7.696135	0.1305	0.220909
1535	2.002853	1.236592	2.330995	2.800053	0.06617
1536	1.87657	1.080399	0.051973	0.995152	1.008075
1537	1.898748	1.278488	1.37819	3.981521	0.033141
1538	2.029391	0.229691	1.205559	0.187908	0.24452
1539	4.901894	3.163284	3.422059	0.007039	0.007165
1540	2.690341	1.67224	1.503115	1.199181	0.112174
1541	1.472912	0.394217	0.851171	1.114886	2.32E-05
1542	0.856295	0.372082	4.663903	1.121351	0.194423
1543	1.354008	0.101721	0.828345	0.450471	1.055856
1544	3.939571	2.751856	0.516214	3.130987	0.682059
1545	2.674475	0.4257	1.339295	2.422571	0.0374
1546	0.777676	0.338861	3.164697	2.874027	2.08E-08
1547	1.228194	0.264173	0.177218	2.36091	0.010021
1548	2.752514	1.38481	4.26385	0.054411	0.004929
1549	4.59126	2.585763	2.713218	2.06881	0.140196
1550	2.025455	1.006195	2.376735	1.731765	0.001664
1551	3.062076	2.678442	0.883413	1.806763	0.273
1552	5.615131	4.843701	7.242146	0.117631	0.000668
1553	1.267251	0.818123	3.537101	2.417908	9.88E-05
1554	2.898552	1.839267	7.478695	0.212064	0.007185
1555	2.82761	1.463213	1.917221	2.164148	0.002218
1556	2.200487	1.547891	1.734767	4.323727	0.003344
1557	6.519135	5.499736	0.265021	0.549802	1.12E-06
1558	1.609372	0.38886	0.0126	1.022338	0.805407
1559	3.238553	2.881235	0.473855	6.283916	1.166016
1560	3.128544	2.00402	1.498453	0.50765	0.00924
1561	3.950394	2.410538	3.068258	2.900106	0.147537

1562	4.230178	2.637456	0.685961	0.692507	0.00976
1563	1.22821	0.184976	0.550351	0.705669	0.290848
1564	3.907218	2.511544	3.121799	4.010829	6.09E-06
1565	3.449518	2.446191	2.248424	2.272963	0.000926
1566	0.963618	0.197577	4.667979	10.66152	0.378172
1567	1.062227	0.119001	5.701054	1.242667	0.012482
1568	1.176802	0.464938	6.353021	1.978065	1.06E-05
1569	1.202831	0.574085	2.458971	2.428057	1.28E-05
1570	2.042351	1.449533	3.224264	3.456502	0.054869
1571	1.427499	0.381179	2.399322	0.01745	0.009551
1572	3.522619	1.290743	0.805987	0.235044	0.918152
1573	1.8594	0.328237	2.672046	2.614219	0.087714
1574	3.665077	2.925476	1.0667	0.396291	0.022698
1575	0.914283	0.341741	6.296316	1.402355	5.15E-05
1576	4.405017	3.144343	4.439819	1.010017	0.495824
1577	2.853742	1.654259	1.586863	1.586752	0.105904
1578	1.136267	0.339594	2.255117	2.505864	0.090372
1579	2.06655	0.837434	1.678877	0.677672	0.003928
1580	5.09892	4.992748	4.12364	0.741573	0.016153
1581	1.493446	0.074924	2.314448	3.109123	0.014682
1582	1.132878	0.366764	7.229699	0.547114	0.007232
1583	3.357206	2.366791	1.04281	5.299254	6.63E-06
1584	1.665529	0.504018	0.732643	1.873817	0.419068
1585	5.678241	3.695036	1.583391	0.891031	1.106156
1586	1.12072	0.099861	1.189791	0.750908	0.170772
1587	2.139021	1.210266	2.120482	2.433555	0.237912
1588	2.293324	1.175784	3.962815	5.849996	0.032962
1589	1.80401	0.533782	0.209968	4.882466	1.06E-06
1590	2.085436	0.638402	3.588005	0.205426	0.002509
1591	2.097765	1.326022	5.434348	2.858792	0.000395
1592	1.244374	0.960853	2.481329	2.206951	0.002235

1593	1.957543	0.757298	2.486024	0.074788	0.000278
1594	1.883208	1.057834	2.337699	1.143846	2.23E-07
1595	5.381946	3.774421	0.250242	2.634989	0.011555
1596	2.155609	1.262837	1.830446	0.138187	0.158115
1597	2.769842	0.66782	0.315984	0.254307	0.227821
1598	3.428682	2.363027	1.116683	1.691611	0.011756
1599	3.535525	2.952743	8.789045	3.38873	6.61E-11
1600	2.751577	1.485873	1.552638	0.805372	0.717762
1601	2.114138	0.852768	2.785635	2.790501	0.164063
1602	1.184191	0.904322	1.927754	0.730489	0.010006
1603	5.718847	4.267578	3.472958	0.761854	0.333678
1604	2.9517	2.175109	5.521359	0.862566	0.267027
1605	4.263011	3.023431	13.40077	5.842659	0.016436
1606	2.008672	0.898027	0.848615	0.863524	0.001918
1607	2.276373	1.052199	1.576012	1.400471	0.00229
1608	2.414766	1.776076	2.741605	6.403045	0.078218
1609	0.994857	0.675075	1.605642	2.997541	0.036975
1610	1.191686	0.173555	4.785214	2.875679	0.174117
1611	1.236811	0.268833	0.39103	5.074326	0.000824
1612	1.875698	0.614811	2.59257	1.631902	0.736346
1613	2.46802	1.058848	2.27224	4.446914	3.38E-05
1614	2.039423	1.271713	3.064579	2.056543	0.350996
1615	2.27402	0.928608	2.349983	0.064145	0.006277
1616	1.969582	0.437144	1.86971	1.446711	0.082547
1617	3.806156	2.191466	1.128926	0.458048	2.17E-05
1618	1.443741	0.22996	1.250095	1.533701	0.004086
1619	1.757589	0.658543	0.278944	3.587778	0.336808
1620	2.293367	0.258161	4.059027	2.746666	6.82E-10
1621	1.822945	1.035926	5.220007	0.317831	0.029161
1622	3.142337	2.065021	10.48694	2.025018	0.117676
1623	1.284337	0.828489	1.363434	0.760038	0.655508

1624	1.486681	0.768905	8.815155	0.547237	0.203354
1625	1.261592	0.281635	1.323048	0.154426	0.863071
1626	1.318085	0.683398	3.612462	0.565629	4.229927
1627	2.698012	1.120613	1.932552	3.077913	0.217556
1628	1.241145	0.476847	4.633599	2.071507	0.12055
1629	3.753555	2.642568	2.47807	3.458693	1.67E-05
1630	0.812593	0.181444	4.606916	4.781491	0.277679
1631	2.08772	0.909319	3.988682	0.576286	0.015659
1632	1.877583	1.486238	0.477604	2.45107	0.485874
1633	1.106485	0.452762	2.768335	2.414558	0.016828
1634	0.952673	0.001037	2.846644	1.822054	0.005402
1635	1.597718	0.339401	1.635403	3.472654	0.000265
1636	2.112202	1.749438	0.285864	0.439675	0.516056
1637	1.89411	0.871114	2.607657	4.628633	0.57275
1638	2.788196	1.801929	1.722834	1.933079	0.659864
1639	1.989494	1.592783	0.493325	4.088664	0.014147
1640	2.578406	0.937917	0.716944	3.228707	7.37E-05
1641	7.495377	5.608548	0.247516	1.302479	1.49156
1642	2.823643	1.207	2.06714	0.973521	0.001134
1643	1.191897	0.527841	3.840903	1.222387	0.001254
1644	1.840752	0.763976	3.241986	9.021601	0.03041
1645	1.455485	0.124895	2.14672	0.191767	0.540601
1646	0.92608	0.342772	1.282961	1.129667	0.013758
1647	3.591619	2.236019	0.271325	1.213154	0.004632
1648	1.312284	0.672025	3.902975	4.53522	0.000176
1649	3.441973	2.366264	3.904511	0.600119	0.066945
1650	3.830208	2.467428	3.823238	0.175588	0.224793
1651	5.33549	4.368432	1.691563	3.643422	0.013283
1652	2.405582	1.434197	1.524182	1.078975	0.095385
1653	0.699142	0.032247	1.337971	3.102326	0.104396
1654	4.160962	2.66251	3.265007	1.026668	3.90E-07
1655	1.567886	1.441516	2.128958	4.621708	0.151524

1656	1.905275	1.580219	9.620926	5.065426	0.034805
1657	3.913611	3.361991	1.943372	0.42227	0.001098
1658	2.88133	1.566056	1.651786	8.180313	0.004042
1659	1.976587	1.267113	1.985846	2.838604	0.071816
1660	5.057007	3.881245	1.116956	1.347623	4.05E-10
1661	2.327975	1.643376	5.998733	3.277961	0.004767
1662	1.078627	0.747564	3.212946	1.091969	0.001154
1663	2.661814	1.52114	0.195924	2.079476	0.008604
1664	1.969682	0.7148	0.389613	3.047476	0.069871
1665	0.274754	0.028139	1.647209	1.118193	0.116122
1666	3.206316	2.264565	5.983342	2.066224	0.000381
1667	3.63464	2.381669	3.960232	4.359794	0.000252
1668	2.946508	1.123358	3.785906	0.068959	0.042106
1669	0.498677	0.152448	0.295503	0.103503	0.022911
1670	5.654724	4.569415	0.694653	0.203878	0.00227
1671	4.611068	3.590478	0.23095	3.040913	0.002433
1672	1.576505	0.826661	0.717795	1.690021	0.215193
1673	1.623311	0.628782	0.361427	0.149924	5.41E-05
1674	4.912983	3.554086	1.198288	2.934757	6.80E-07
1675	5.133035	4.543048	2.321383	0.931741	0.059377
1676	4.841373	4.045204	6.890589	0.884974	0.005628
1677	0.634642	0.366117	1.610537	1.059938	0.030259
1678	3.14944	1.948883	2.629386	7.608155	0.103862
1679	2.156919	0.453232	2.129682	2.610716	0.471211
1680	1.513443	1.230198	7.673418	0.621069	0.002071
1681	1.260404	0.944103	6.309266	0.146584	1.118882
1682	2.887042	1.542946	6.380198	1.360181	1.17372
1683	2.098121	0.801384	9.69928	1.64538	0.004646
1684	3.09924	1.91934	1.744656	0.465499	0.267164
1685	0.939037	0.213361	5.206888	1.94602	0.093093
1686	1.409266	0.495147	1.641093	2.185123	0.023149

1687	1.334818	0.24781	0.405432	5.753493	0.000275
1688	1.607854	0.809894	5.683478	3.006824	0.062841
1689	2.766108	1.333186	0.368318	0.554258	1.076454
1690	3.96138	2.873621	2.683186	9.231698	0.148058
1691	2.195111	0.670818	6.737893	0.301951	0.029163
1692	3.71799	2.784747	2.363034	0.576187	0.001824
1693	2.701491	1.825367	4.930391	2.508632	3.086956
1694	3.239036	2.753116	1.70549	0.772596	0.048871
1695	1.491437	0.370333	3.937794	2.573309	0.003784
1696	3.464288	2.443368	8.035606	0.24722	0.007246
1697	4.266261	2.88153	2.84403	1.006756	0.030888
1698	2.515246	1.384676	6.532563	4.706995	0.005216
1699	5.127339	4.119206	3.319786	0.959986	3.47E-06
1700	2.889742	1.580085	1.37836	0.424069	0.168374
1701	4.791815	4.294302	2.611274	1.929615	0.006225
1702	3.732935	3.068742	4.424908	7.381968	0.044623
1703	0.988491	0.373061	1.423112	4.411152	0.202688
1704	5.532845	4.078725	8.361445	0.241861	2.35E-06
1705	2.964973	2.021663	2.256382	2.070548	0.007207
1706	2.420738	1.224863	0.07322	1.495375	3.008424
1707	1.18379	0.442166	3.191857	0.512305	6.48E-09
1708	1.288154	0.612654	3.392279	1.869621	0.000181
1709	1.976206	0.759308	4.398464	2.967635	0.009523
1710	1.646448	0.925897	0.303423	2.47337	0.091622
1711	1.636836	0.424298	1.154742	4.230827	0.000655
1712	0.572053	0.166767	6.141616	2.410433	0.23875
1713	3.695818	2.318953	1.815821	1.704663	1.233745
1714	1.577059	0.939191	9.119349	7.478628	0.038387
1715	2.253279	1.518767	3.922009	0.03332	0.351387
1716	2.840862	1.537569	2.224865	3.858244	0.021789
1717	3.641076	3.292282	6.744211	3.213075	0.422926

1718	1.588987	0.897683	15.21195	1.464171	0.001414
1719	1.691919	0.712442	3.010353	0.347536	0.000641
1720	5.370558	3.744284	4.192658	6.876396	0.004378
1721	2.703328	1.344699	1.715494	0.131809	5.05E-05
1722	4.96214	3.697011	3.780784	4.247184	2.89E-07
1723	4.781388	3.493108	3.010647	0.673863	3.47E-05
1724	1.283999	0.386224	3.144461	1.493693	0.000525
1725	0.525876	0.326673	0.436846	2.64078	0.124235
1726	7.943025	7.449752	0.892786	3.099894	0.000902
1727	1.073778	0.165503	2.708844	0.961079	0.163789
1728	1.229774	0.854872	0.886482	6.162544	0.000258
1729	3.903018	2.776425	1.401942	0.94644	0.001463
1730	2.280738	1.628547	2.96441	3.172944	1.75E-09
1731	1.763314	0.76897	0.878954	4.416673	0.000175
1732	8.007845	6.202823	1.601843	4.405948	0.104287
1733	1.389126	0.205068	1.280358	0.694429	1.87E-05
1734	1.785569	0.599701	13.00847	3.583504	0.275067
1735	2.922286	1.812118	0.764877	1.189791	0.006711
1736	2.576452	1.82093	3.725651	0.437153	0.040477
1737	1.788069	0.630438	0.39427	1.792651	0.13177
1738	3.514113	2.917549	1.078304	0.057869	0.10871
1739	2.881081	2.168224	1.552261	5.015472	0.034696
1740	4.902041	3.653593	2.615188	0.967912	0.052779
1741	2.87711	1.881538	1.954172	0.029989	0.000173
1742	5.924765	4.841053	3.828275	3.118359	2.340802
1743	2.255829	0.834483	2.545529	0.371701	0.022655
1744	4.180509	3.282642	2.098319	0.457344	0.001913
1745	1.183355	0.672721	3.92217	1.274345	0.094742
1746	1.371003	0.309137	1.436281	3.271388	0.485297
1747	1.892492	0.781039	0.961131	0.694444	8.80E-05
1748	3.542589	2.430287	0.324407	0.369558	0.00057

1749	1.922211	0.387435	2.973111	0.293124	0.003757
1750	1.417081	0.565321	5.200712	1.481231	0.063761
1751	2.285613	0.338021	2.138952	2.276813	0.006992
1752	3.400269	2.501736	5.290664	0.305161	0.000147
1753	2.022597	1.001412	3.951787	3.998944	0.011035
1754	1.907658	1.701621	4.278072	0.567495	0.001744
1755	5.282636	4.538186	7.82847	3.734582	7.76E-07
1756	2.232856	0.959797	1.386711	0.337877	0.090846
1757	2.778611	1.552895	4.070965	0.10099	3.29E-05
1758	3.804509	2.672479	2.425341	0.58497	0.003767
1759	1.772086	0.771333	4.118435	0.106028	0.430351
1760	0.799987	0.22431	0.285276	7.398755	0.030781
1761	3.08429	1.843052	0.607214	3.698294	1.544559
1762	5.192194	4.219645	1.140526	1.939441	0.259027
1763	3.28481	2.002554	8.273449	4.509899	0.041523
1764	2.168165	1.002905	2.1606	6.329187	0.001951
1765	1.537521	0.400337	13.45481	3.007463	0.001977
1766	3.137022	2.223362	2.690441	4.336611	1.284874
1767	1.507955	0.189691	4.232921	0.096405	0.006164
1768	4.137957	3.423195	2.355646	0.683773	0.034899
1769	4.257455	2.926041	4.54681	0.343192	0.041619
1770	1.95366	0.557399	7.875698	0.70185	0.649759
1771	6.698523	5.945613	1.962324	1.806276	0.001144
1772	1.278668	0.140654	9.58513	0.338931	0.003351
1773	2.297755	1.065848	1.422766	3.360792	0.051879
1774	1.241036	0.217366	3.413591	0.014467	1.05E-06
1775	0.874064	0.59127	1.850437	0.085312	2.25E-05
1776	1.308398	0.137038	1.270388	5.657264	0.00147
1777	2.234752	0.547989	3.541229	3.111188	4.60E-05
1778	3.69856	3.020663	0.84782	3.153936	0.020494
1779	1.42695	0.671763	2.795195	1.066487	0.00198
1780	1.009669	0.313265	0.318137	5.033932	0.142398

1781	1.125233	0.473202	4.158419	0.311856	0.077192
1782	1.166708	0.320114	5.018818	1.13716	0.236984
1783	1.781086	0.953254	16.3033	0.20685	0.453616
1784	1.369003	0.684868	1.241661	5.321569	0.570878
1785	2.053536	1.348389	2.58608	6.159973	0.075146
1786	1.073424	0.285207	0.563776	4.272814	5.36E-06
1787	1.592646	0.592561	3.095377	1.226894	0.011682
1788	1.861878	0.130344	2.01675	4.378592	6.31E-06
1789	1.130502	0.298817	2.247516	0.923308	0.003513
1790	2.258209	1.758044	0.948791	3.893874	0.000498
1791	2.110006	0.580348	1.864878	1.518411	8.08E-05
1792	3.90188	3.038862	4.432054	1.339615	5.16E-06
1793	1.630072	0.685551	4.099768	2.235392	0.084214
1794	1.763879	0.764723	3.873016	1.998761	0.016129
1795	3.851421	2.749227	4.912545	1.452245	0.02408
1796	2.070684	0.997993	2.115086	0.963197	0.313698
1797	3.371628	2.32852	0.983602	0.32007	0.104826
1798	1.751936	1.164808	2.900308	1.370876	0.793827
1799	3.557204	2.309227	5.384733	1.50843	0.012737
1800	3.908404	3.089259	2.148997	4.999444	0.191226
1801	2.915373	1.339708	2.274908	2.820292	0.025455
1802	3.354393	2.001504	3.777691	0.166787	0.012747
1803	2.005207	0.688869	4.600225	0.953866	0.025497
1804	6.210943	5.371189	1.51456	7.077649	1.093868
1805	1.729967	0.726513	1.277346	1.024759	0.011726
1806	0.825403	0.112725	0.82824	1.693017	0.00011
1807	2.800898	1.376088	0.395745	2.413463	0.191611
1808	2.321017	0.851499	6.205167	1.423746	1.62833
1809	2.367638	1.442401	4.442512	1.778824	0.374721
1810	1.466881	0.525471	0.847019	1.823458	0.444692
1811	2.929901	1.989358	2.924603	0.084673	3.20E-07

1812	2.719339	1.895129	1.696222	0.269838	4.34E-09
1813	2.955073	1.258403	2.871814	3.635677	3.32E-06
1814	2.115245	1.179383	0.542386	1.668523	0.278959
1815	2.795037	1.461309	0.378957	1.705451	0.013132
1816	2.110426	1.411013	6.384437	1.090548	0.385935
1817	3.633982	2.743564	3.545178	0.098932	1.55E-05
1818	0.835623	0.393429	1.955069	6.247898	7.00E-05
1819	0.902099	0.116014	1.173007	0.148988	0.033778
1820	1.639785	1.083626	3.944225	1.573905	0.592465
1821	1.062226	0.274226	0.820549	0.253292	0.017648
1822	4.3381	3.720685	2.891796	0.715583	6.79E-05
1823	6.574819	4.799978	4.45578	0.349512	0.017009
1824	2.401802	0.974295	4.365293	1.245606	6.12E-05
1825	3.669317	3.069286	3.345442	1.86693	0.373086
1826	3.077104	2.314922	1.820115	1.448773	7.85E-09
1827	2.289723	1.47698	2.2565	3.679205	0.090578
1828	1.652154	1.159255	9.567417	5.291505	0.015195
1829	2.075302	0.654175	1.070415	3.068937	0.006412
1830	2.584416	1.490043	4.951196	0.173701	0.026241
1831	4.016879	1.911606	0.039388	5.703554	0.036622
1832	1.219472	0.235965	1.3455	5.567945	0.024859
1833	2.486449	1.403177	9.551795	1.92018	0.005042
1834	2.328182	1.31705	3.144565	2.656203	0.009266
1835	5.461699	4.823723	0.549146	0.818718	0.028966
1836	2.184695	0.68908	5.853997	0.500367	2.618862
1837	2.78226	1.236759	3.023177	0.580659	1.61E-06
1838	1.071242	0.668949	3.428014	1.130571	9.01E-06
1839	1.631512	1.300013	0.811873	1.026962	0.440955
1840	1.665021	0.315829	1.220526	0.342175	0.034719
1841	1.867044	0.565559	1.734741	4.492998	4.20E-05
1842	1.575235	0.197505	1.559741	1.778587	4.44E-05

1843	1.269674	0.548714	5.205585	1.451041	0.006016
1844	1.514683	0.314908	11.13505	2.910458	0.248025
1845	1.7596	0.168071	1.398339	1.200332	3.23E-05
1846	2.822782	1.492816	1.396751	1.606236	0.001723
1847	3.346509	2.084946	8.958947	2.236048	0.02036
1848	2.478905	1.151186	1.669012	1.429279	0.000231
1849	1.482606	0.587919	6.066683	1.928534	0.00948
1850	0.774487	0.456373	1.250179	3.810359	2.200078
1851	2.296891	1.572322	1.145826	0.314182	0.075611
1852	0.997103	0.07671	2.163051	0.671201	6.92E-06
1853	4.005585	2.929352	1.089137	0.459031	0.899027
1854	2.218306	1.175412	1.774574	0.574423	1.95E-05
1855	1.981183	1.002955	0.210374	1.755957	0.212416
1856	3.814342	2.725835	1.355791	1.882933	7.22E-09
1857	0.645238	0.105102	2.280161	0.341775	8.09E-05
1858	0.74418	0.109751	3.895281	2.388225	0.258612
1859	2.654159	1.604475	2.363968	4.035466	0.4324
1860	2.685395	2.009696	3.79538	1.803272	0.026561
1861	2.018881	1.099991	2.94638	0.397306	0.003293
1862	2.734561	1.975376	3.014867	2.221207	3.99E-09
1863	4.164419	2.767541	5.061229	0.047671	0.191299
1864	5.108875	3.783845	1.460362	2.063837	0.000961
1865	5.243775	3.820968	2.355323	0.650865	0.001365
1866	1.139038	0.42022	3.576248	4.207737	0.000713
1867	3.795973	2.676968	2.042383	1.076823	0.000103
1868	6.159749	5.185916	14.03808	0.765361	0.047552
1869	1.072972	0.32852	0.29453	0.671093	9.76E-09
1870	0.926186	0.194983	5.288552	0.273116	3.13E-08
1871	5.806107	5.474805	5.264452	1.834604	4.51E-05
1872	3.202885	1.184663	5.318452	3.623693	4.70E-05
1873	2.436247	2.06	0.057776	1.07038	2.09E-05

1874	3.207824	2.096924	1.682836	0.645254	0.001996
1875	6.738495	5.173742	1.591179	1.751129	0.0784
1876	2.878719	1.117202	1.131615	0.000948	0.059856
1877	1.719212	0.670385	1.36131	4.511817	0.008621
1878	2.445511	1.245958	1.107248	4.939889	7.36E-07
1879	1.685133	1.14458	2.082853	2.441428	0.102522
1880	1.063056	0.667127	0.590963	1.289792	1.08E-07
1881	2.216187	0.89805	1.41274	0.644765	0.00485
1882	1.507187	0.244188	2.637611	1.549122	0.002155
1883	0.612616	0.609375	0.907636	3.1015	0.148861
1884	1.92346	0.46914	1.441359	5.826055	0.139992
1885	2.373933	0.775611	0.266618	0.837866	0.015624
1886	4.846027	3.994831	0.357387	0.359098	1.36E-05
1887	5.38613	4.373639	0.213623	1.088667	0.063341
1888	4.31443	3.119299	2.867814	4.040816	0.870376
1889	2.013	1.294641	2.952912	0.561676	0.049185
1890	2.057071	1.180236	2.587473	3.013843	9.65E-08
1891	3.089715	1.11519	2.668722	3.38535	0.024946
1892	2.5672	1.437694	3.075693	3.875699	0.059295
1893	3.527753	3.208498	1.646993	0.613427	0.060546
1894	3.842765	2.054833	1.682573	0.182087	0.002539
1895	1.293272	1.052326	0.277048	0.292148	0.09297
1896	1.815224	1.072723	1.003574	6.271795	0.039408
1897	5.494967	4.311795	5.543292	4.29005	0.290289
1898	0.10744	0.392414	0.644474	1.359387	1.190096
1899	2.401618	1.448521	0.972224	0.35145	0.032285
1900	3.302281	2.068322	0.471507	1.571214	0.00915
1901	1.035196	0.345783	0.356886	0.158885	0.001388
1902	2.633468	1.657332	1.496867	4.430476	0.019137
1903	1.64136	0.575592	2.442776	7.041494	0.002467
1904	3.391992	3.193118	2.330759	0.868526	3.30E-05
1905	1.430596	0.190203	1.70474	0.941545	0.032757

1906	3.163228	1.564852	1.803158	3.597642	0.074242
1907	2.882782	1.671126	3.198196	1.721138	0.053645
1908	1.28811	0.432671	2.872607	0.169757	0.000959
1909	2.13705	1.161792	0.82006	3.928626	2.770912
1910	5.163414	4.009937	0.20619	3.607395	8.47E-06
1911	3.65731	2.347854	2.833453	4.648572	0.000185
1912	2.037272	0.349259	10.94543	0.516785	0.641699
1913	2.696199	1.526843	1.775777	3.07313	0.13432
1914	4.69512	3.851014	3.947867	3.013903	1.01E-05
1915	1.421521	0.111137	0.995172	2.062721	0.639458
1916	1.768164	0.502833	3.223209	1.087336	0.213352
1917	2.125781	0.561422	5.049522	1.849325	0.344032
1918	1.830857	0.363095	3.21304	0.069014	0.4091
1919	3.537234	2.314007	1.67575	0.229097	1.00E-05
1920	1.880925	0.989381	3.479718	1.810254	2.12E-14
1921	4.728067	3.861481	5.453207	0.74936	0.017658
1922	2.786103	1.592266	6.041209	0.051549	0.104994
1923	2.605505	1.377636	3.70552	1.556049	0.037214
1924	1.009569	0.667422	7.334782	0.175827	0.002575
1925	1.777407	1.393554	3.051128	5.874029	0.372461
1926	1.423955	0.025029	4.01174	7.330415	0.306837
1927	2.094803	1.574548	0.347663	4.456253	5.62E-06
1928	2.528502	1.006427	4.033281	3.076817	0.00086
1929	3.481104	2.601792	1.028632	6.400263	0.03668
1930	1.239253	1.309199	4.472025	2.532099	9.51E-05
1931	2.907018	1.702506	2.805274	1.253793	3.78E-06
1932	1.803399	1.422508	2.859975	9.796565	0.089995
1933	3.014726	2.231163	3.227032	1.524076	0.005016
1934	2.724849	1.511699	1.018106	3.968746	0.001525
1935	1.309796	0.503556	3.776213	3.986588	0.257096
1936	3.418969	2.389936	1.097552	2.888049	0.005102

1937	0.820476	0.366395	5.816173	4.302326	0.01355
1938	2.304268	1.626506	4.231888	1.687598	0.141721
1939	3.486504	1.96775	3.525108	0.436824	0.034325
1940	3.331624	1.289238	2.767612	8.130857	0.006755
1941	2.240557	1.206501	1.915075	1.187446	0.267341
1942	3.828154	2.418756	1.609159	1.677827	0.002094
1943	2.708543	1.901661	0.261179	1.34744	0.021561
1944	2.909507	1.739118	2.581511	0.965844	6.89E-09
1945	1.486599	0.411156	3.21738	3.653822	0.39521
1946	1.208979	0.424527	0.788217	0.364922	0.000186
1947	5.251677	4.869684	1.452345	3.488514	0.444972
1948	1.896966	0.235111	2.227482	0.798435	0.00055
1949	0.800985	0.305464	0.490154	0.513737	0.204387
1950	1.7233	0.262171	1.0867	1.955679	0.005152
1951	2.565328	1.729254	0.50529	1.433066	1.187483
1952	2.966225	1.311162	5.825188	0.538294	1.28E-05
1953	5.477143	4.71939	4.103812	0.479566	0.012447
1954	1.33624	0.15314	5.140174	2.207542	0.046577
1955	3.028664	1.512747	5.521886	1.591559	0.000171
1956	1.982733	0.661312	4.251462	6.157307	0.001146
1957	1.958433	0.772114	3.088997	1.715257	0.004449
1958	2.493625	1.420695	0.783224	6.196168	0.15589
1959	1.21139	0.62644	4.285312	1.435638	0.112102
1960	4.719582	3.416587	7.586726	1.863505	0.515023
1961	4.288429	3.317816	5.955193	1.972074	0.755968
1962	1.852857	1.560525	1.365727	4.75202	0.33739
1963	2.020552	0.981703	1.884436	0.241185	0.377738
1964	2.621691	1.122658	4.384255	2.651128	0.000644
1965	2.843408	1.812251	3.41861	0.630564	0.009145
1966	1.561956	0.365857	5.753594	3.326079	0.031482
1967	3.216737	2.544185	10.46253	1.428364	0.028766

1968	5.23937	4.019947	2.65941	2.727468	0.023866
1969	4.716768	3.12845	0.899665	5.028097	0.063364
1970	1.998591	0.994803	2.179971	0.540746	0.186591
1971	0.877911	0.299744	0.30385	7.442816	0.000618
1972	1.669886	0.962061	4.66896	0.321076	0.003432
1973	3.00049	1.659812	1.576984	0.15739	1.02E-12
1974	1.495941	1.172625	2.480413	0.303331	1.62E-07
1975	2.280904	1.101802	2.588111	0.766146	0.51895
1976	2.30264	1.285933	9.754484	5.761432	0.000549
1977	0.685286	0.213985	1.739271	1.979675	0.104127
1978	4.175703	2.471789	0.876007	0.321832	0.007796
1979	1.687951	0.347932	1.13372	0.218201	5.58E-05
1980	4.739321	3.511267	1.096458	1.633839	7.46E-08
1981	6.07761	4.894931	1.808103	1.486947	0.120216
1982	1.360409	0.539185	2.027343	3.779734	0.269109
1983	1.453395	0.746311	2.595271	0.811476	0.000142
1984	3.634693	2.356474	11.24485	0.675442	0.001135
1985	2.528622	2.098622	0.011725	0.430561	0.630359
1986	1.384797	0.38004	5.055856	1.811551	0.000375
1987	3.110473	2.009609	3.62016	2.290887	7.00E-05
1988	2.679951	1.248428	5.015007	0.577928	0.069305
1989	3.854493	2.888359	2.917737	2.004714	0.035995
1990	2.871681	1.156058	2.284082	5.625571	0.005874
1991	2.125982	0.858879	3.386494	2.092853	7.65E-06
1992	0.227964	0.245488	2.585901	3.695878	0.317027
1993	6.612163	6.119507	7.031412	1.374016	0.064573
1994	3.848889	2.874669	1.237303	3.568821	0.017366
1995	1.223584	0.308704	2.746848	1.094733	2.89E-07
1996	1.654883	0.288971	8.340601	1.103556	0.286889
1997	1.974016	1.436765	0.078685	3.865243	0.0083
1998	4.106063	3.276552	2.750344	2.858694	0.008526

1999	1.939484	0.799748	1.828551	0.473701	6.31E-08
2000	2.621439	0.763924	4.348351	1.326783	0.149824