

Effects of sample size and dispersion on quantile-based plots for detecting normality

¹Isaac O. Ajao, ²Awogbemi C. Adeyeye and Urama Kenneth Ugochukwu³

¹Department of Mathematics and Statistics, The Federal Polytechnic, Ado-Ekiti, Nigeria

²Department of Statistics, National Mathematical Centre, Abuja, Nigeria

³Department of Statistics, Michael Okpara University of Agriculture, Umudike, Nigeria

Corresponding Author: **Urama Kenneth Ugochukwu**

Abstract

A lot of researchers handling data want their data tested for normality before proceeding to further statistical analysis. The classical tests for the assessment of normality among others are Kolmogorov-Smirnov (K-S) test, Lilliefors corrected K-S test, Shapiro-Wilk test, Shapiro-Francia test, Anderson-Darling test, Cramer-von Mises test, D'Agostinoskewness test, Anscombe-Glynn kurtosis test, D'Agostino-Pearson omnibus test, and the Jarque-Bera test. The visual methods commonly used are the histogram, boxplot, pp-plot, qqplot, and the stem-and-leaf plot. This paper seeks to find out the effect of sample and dispersion on quantile based plots for detecting normality in montecarlo simulated and the transformed data. It was observed that as the sample size increases the data approaches normality, while it suffers departure as standard deviation increases. It is therefore recommended that the visual methods, especially the qq-plot be used for detecting normality only when the sample size is low and the standard deviation is high.

Keywords: Normality, QQ-plot, Sample Size, Dispersion, Classical Tests

1.0 Introduction

The statistical methods are based on various assumptions that uphold the methods. One of them is the normality assumption. It is often required to check the normality in many data analyses, although normality is implicitly or conveniently assumed in reality. If the assumption is violated, interpretations and inferences based on the models are not reliable, if not valid. There are two ways of checking normality. The graphical methods visualize differences between the empirical distribution and the theoretical distribution like a normal distribution. The numerical methods conduct statistical tests on the null hypothesis that the variable is normally distributed. The graphical methods visualize the distribution using plots. They are grouped into the descriptive and theoretical. The former method is based on the empirical data, whereas the latter considers both empirical and theoretical distributions.

1.1 Descriptive plots and Theoretical Plots

The frequently used descriptive plots are the stem-and-leaf-plot, (skeletal) boxplot, dot plot, and histogram. When N is small, a stem-and-leaf plot or dot plot is useful to summarize data; the histogram is more appropriate for large N samples. A stem-and leaf plot assumes continuous variables, while a dot plot works for categorical variables. A box plot presents the 25 percentile, 50 percentile (median), 75 percentile, and mean in a box. If a variable is normally distributed, its 25 and 75 percentile become symmetry, and its median and mean are located at the same point exactly in the middle. The P-P plot and Q-Q plot are more commonly used to check normality than the descriptive plots. The probability-probability plot (P-P plot or percent plot) compares the empirical cumulative distribution function of a variable with a specific theoretical cumulative distribution function (e.g., the standard normal distribution function). Similarly, the quantile-quantile plot (Q-Q plot) compares ordered values of a variable with quantiles of a specific theoretical distribution (i.e., the normal distribution). If two distributions match, the points on the plot will form a linear pattern passing through the origin with a unit slope. So, the P-P plot and the Q-Q plot are used to see how well a

theoretical distribution models the empirical data. Although visually appealing, these graphical methods do not provide objective criteria to determine the normality of variables. Interpretations are matter of judgments. Therefore this paper focuses on the necessity of numerical methods to determine normality rather than the graphical methods. It is also to compare numerical results with judgment.

1.2 Theoretical Statistics

The numerical methods of testing normality include the Kolmogorov-Smirnov (K-S) (Smirnov, 1948) D test (Lilliefors test, Lilliefors, 1967), Shapiro-Wilk’ test, Anderson-Darling test, and Cramer-von Mises test (SAS Institute 1995, von Mises, 1928). The K-S D test and Shapiro-Wilk’ W test are commonly used. The K-S, Anderson-Darling (Anderson and Darling, 1954), and Cramer-von Misers (Cramer, 1928) tests are based on the empirical distribution function (EDF), which is defined as a set of N independent observations x1, x2, ...xn with a common distribution function F(x).

Table 1: Numerical tests of normality

Test	Statistic	Sample Size (N)	Distn
Jarque-Bera (S-K) test	χ^2		$\chi^2 (2)$
Shapiro-Wilk	W	$7 \leq N \leq 2000$	-
Shapiro-Francia	W	$5 \leq N \leq 5000$	-
Kolmogorov-Smirnov	D	> 2000	EDF
Cramer-volMises	W ²	> 2000	EDF
Anderson-Darling	A ²	> 2000	EDF

2.0 Methodology

The Shapiro-Wilk statistic (1965) is the ratio of the best estimator of the variance to the usual corrected sum of squares estimator of the variance (Royston, 1982). The statistic is positive and less than or equal to one; being close to one indicate normality. The W statistic requires that the sample size need to greater than or equal to seven and less than or equal to 2,000 (Royston, 1992).

$$W = \frac{\left(\sum_{i=1}^n a_i x_{(i)} \right)^2}{\sum_{i=1}^n (x_i - \bar{x})^2}, \tag{1}$$

where $x_{(i)}$ is the i th order statistic i.e. the i th-smallest number in the sample; $\bar{x} = (x_1 + \dots + x_n)/n$ is the sample mean; the constant a_i are given by (Shapiro-Wilk, 1965):

$$(a_1, a_2, \dots) = \frac{m^T V^{-1}}{(m^T V^{-1} V^{-1} m)^{1/2}}, \tag{2}$$

where $m = (m_1, \dots, m_n)^T$ and m_1, \dots, m_n are the expected values of the order statistics of independent and identically distributed random variables sampled from the standard normal distribution, and V is the covariance matrix of those order statistics.

The Shapiro-Francia test is an approximate test that modified the Shapro-Wilk test. The statistic was developed by Shapiro and Francia (1972) and Royston (1983). Let x_i be the i th

ordered value from our size- n sample, also $m_{i:n}$ be the mean of the i th order statistic when making n independent draws from a normal distribution. The Pearson correlation coefficient between x and the m is then given as:

$$W' = \frac{\text{cov}(x, m)}{\sigma_x \sigma_m} = \frac{\sum_{i=1}^n (x_i - \bar{x})(m_i - \bar{m})}{\sqrt{\left[\sum_{i=1}^n (x_i - \bar{x})^2 \right]} \times \sqrt{\left[\sum_{i=1}^n (m_i - \bar{m})^2 \right]}} \quad (3)$$

Under the null hypothesis that the data is drawn from a normal distribution, this correlation will be strong, so W' cluster just under 1, with the peak becoming narrower and closer to 1 as n increases. If the data deviate strongly from a normal distribution, W' will be smaller (Shapiro and Francia, 1972).

4. Data Analysis and Results

4.1 Monte Carlo Simulation Setup

To measure the effect of sample size on quantile based plots for detecting normality, we simulated random numbers following the normal distribution with $\mu = 50$, $\sigma = 2$ for various sample sizes ($n = 20, 50, 100, 250, 500, 1000$) and sets of transformed variables (cubic, square, square root, log, 1/square root, inverse, 1/square, and 1/cubic). Standard deviations of 3 and 5 were introduced into the simulation in order to test for the effect of dispersion. All analyses were done using MATLAB R2017a and STATA 12 SE.

4.2 Empirical Results

Table 1: Normality tests on transformed data when $n = 20$ and $n = 50$

Sample size	Transformation	Formula	chi2	Pr(chi2)	Swilk	Pr(Swilk)	Sfrancia	Pr(francia)
20	cubic	x^3	0.6200	0.7340	0.9789	0.9192	0.9874	0.9764
	square	x^2	0.5400	0.7650	0.9747	0.8496	0.9827	0.9209
	identity	x	0.5100	0.7750	0.9773	0.8949	0.9856	0.9591
	square root	$\text{sqrt}(x)$	0.5100	0.7740	0.9793	0.9250	0.9879	0.9802
	log	$\text{log}(x)$	0.5200	0.7690	0.9795	0.9273	0.9882	0.9818
	1/square root	$1/\text{sqrt}(x)$	0.5400	0.7620	0.9794	0.9261	0.9881	0.9816
	inverse	$1/x$	0.5700	0.7530	0.9791	0.9214	0.9878	0.9795
	1/square	$1/(x^2)$	0.6300	0.7280	0.9776	0.9002	0.9864	0.9677
	1/cubic	$1/(x^3)$	0.7200	0.6970	0.9753	0.8597	0.9840	0.9398
	50	cubic	x^3	0.5500	0.7580	0.9599	0.0885	0.9729
square		x^2	1.1600	0.5610	0.9696	0.2244	0.9690	0.1829
identity		x	1.9000	0.3870	0.9654	0.1508	0.9636	0.1139
square root		$\text{sqrt}(x)$	2.3100	0.3150	0.9567	0.0647	0.9605	0.0862
log		$\text{log}(x)$	2.7500	0.2530	0.9531	0.0460	0.9570	0.0636
1/square root		$1/\text{sqrt}(x)$	3.2100	0.2010	0.9493	0.0319	0.9531	0.0459
inverse		$1/x$	3.7000	0.1570	0.9451	0.0217	0.9490	0.0325
1/square		$1/(x^2)$	4.5200	0.1040	0.9361	0.0095	0.9400	0.0156
1/cubic		$1/(x^3)$	5.3400	0.0690	0.9261	0.0039	0.9299	0.0072

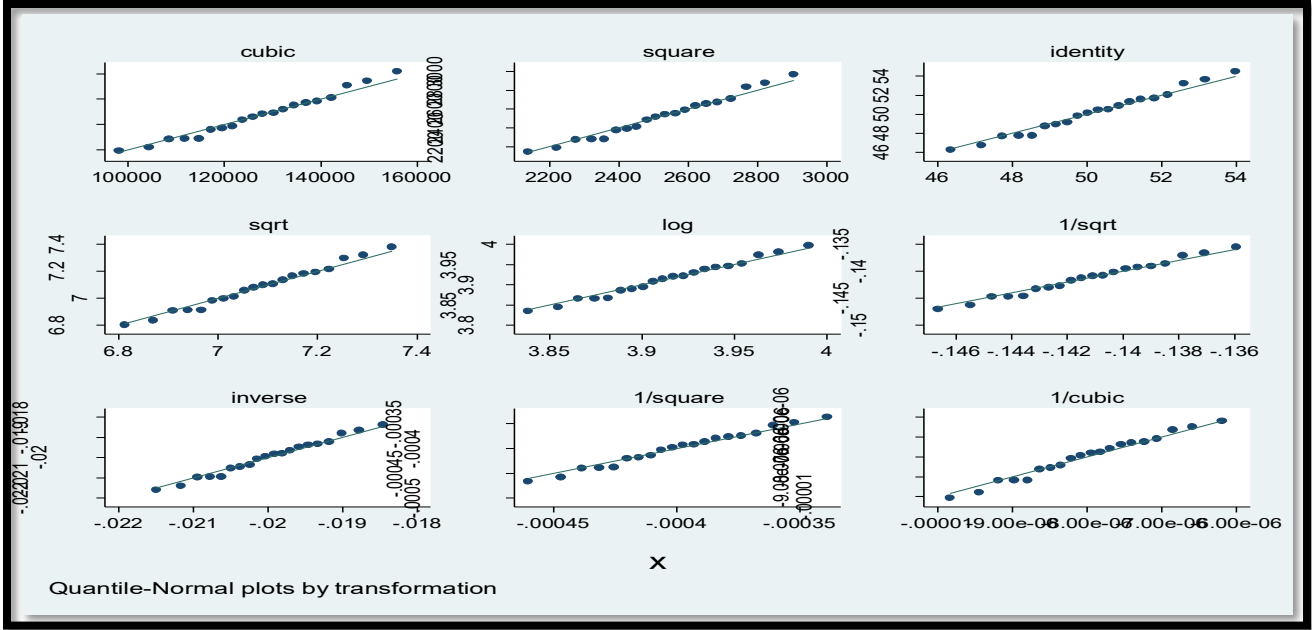


Fig. 1: Quantile plots of transformed data when n=20

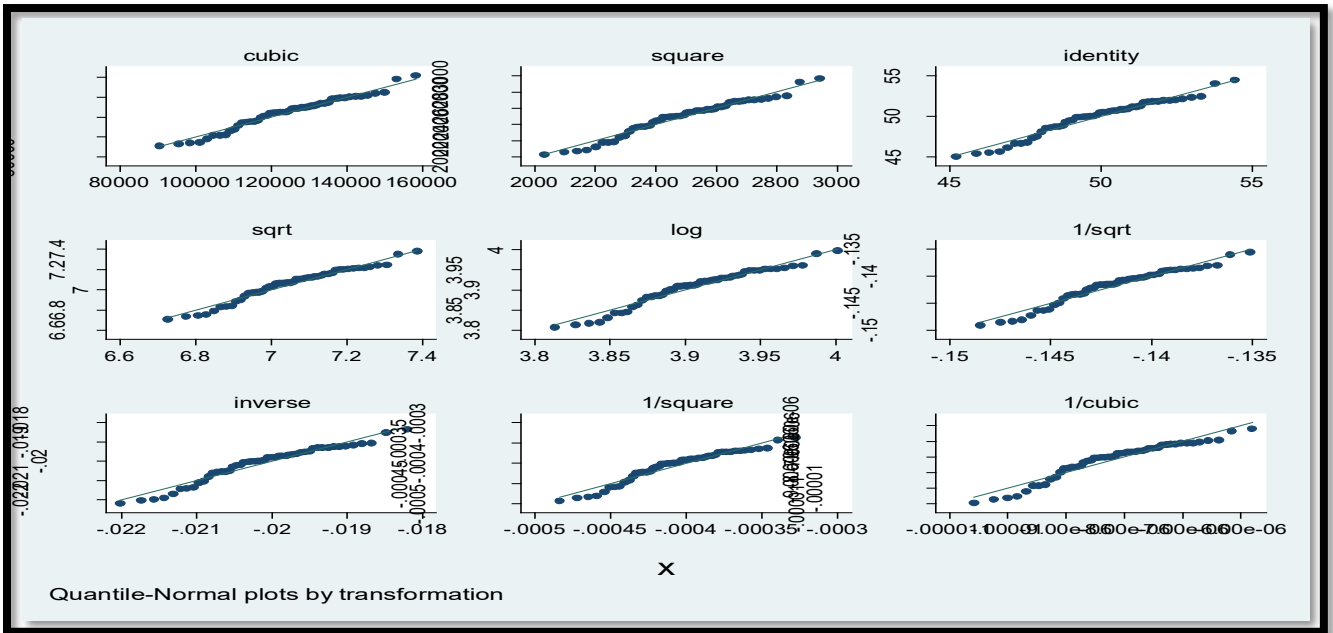


Fig. 2: Quantile plots of transformed data when n=50

Table 2: Normality tests on transformed data when n = 100 and n = 250

Sample size	Transformation	Formula	chi2	Pr(chi2)	Swilk	Pr(Swilk)	Sfrancia	Pr(francia)
100	cubic	x^3	1.5700	0.4560	0.9907	0.9171	0.9905	0.8401
	square	x^2	0.6200	0.7330	0.9929	0.7284	0.9927	0.6134
	identity	x	0.3400	0.8430	0.9935	0.8832	0.9933	0.7921
	square root	\sqrt{x}	0.4500	0.7990	0.9932	0.9019	0.9930	0.8199
	log	$\log(x)$	0.7100	0.7000	0.9925	0.8610	0.9924	0.7681
	1/square root	$1/\sqrt{x}$	1.1400	0.5670	0.9915	0.7862	0.9913	0.6821
	inverse	$1/x$	1.7100	0.4250	0.9901	0.6732	0.9899	0.5662
	1/square	$1/x^2$	3.3100	0.1910	0.9861	0.3821	0.9858	0.3080
	1/cubic	$1/x^3$	5.2200	0.0740	0.9806	0.1504	0.9802	0.1234
250	cubic	x^3	0.7000	0.7060	0.9954	0.6552	0.9957	0.6421
	square	x^2	0.0100	0.9940	0.9961	0.7833	0.9966	0.7923
	identity	x	0.3700	0.8300	0.9955	0.6801	0.9961	0.7058
	square root	\sqrt{x}	0.9000	0.6370	0.9947	0.5419	0.9954	0.5737
	log	$\log(x)$	1.6500	0.4390	0.9937	0.3722	0.9943	0.4056
	1/square root	$1/\sqrt{x}$	2.6000	0.2730	0.9923	0.2163	0.9930	0.2457
	inverse	$1/x$	3.7500	0.1540	0.9906	0.1066	0.9913	0.1283
	1/square	$1/x^2$	6.3700	0.0410	0.9863	0.0172	0.9870	0.0245
	1/cubic	$1/x^3$	9.2500	0.0100	0.9809	0.0019	0.9816	0.0034

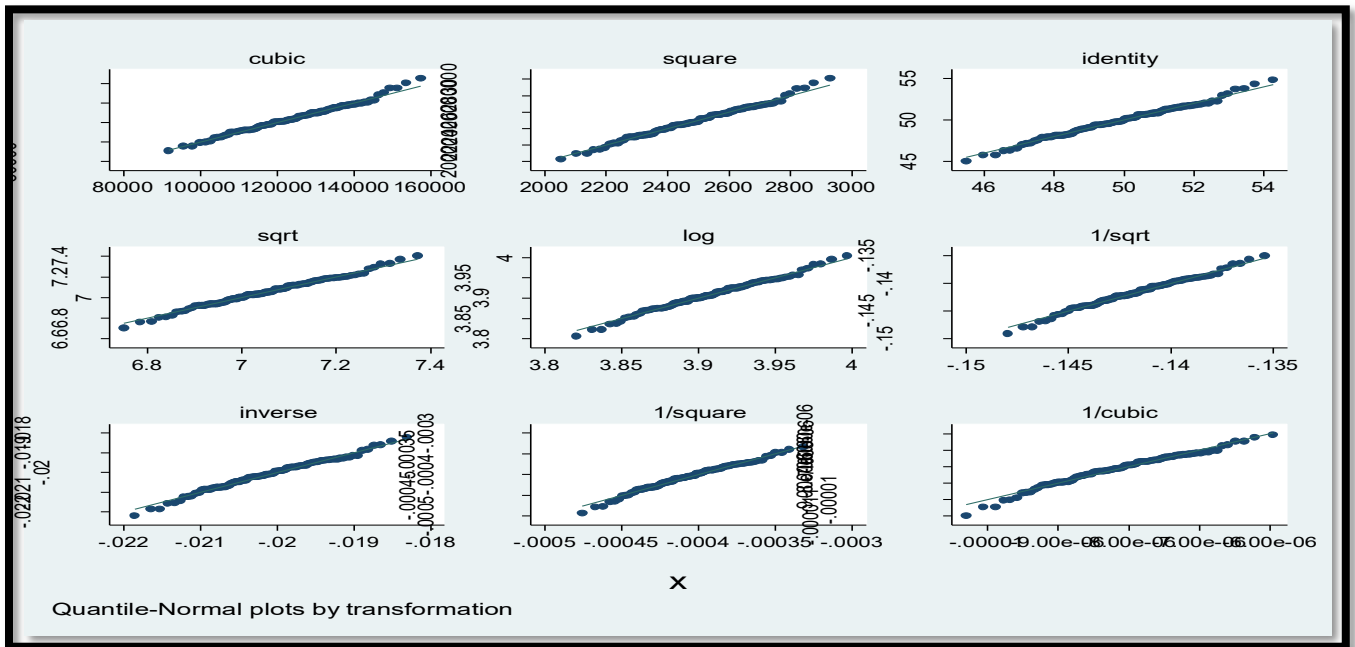


Fig. 3: Quantile plots of transformed data when n=100

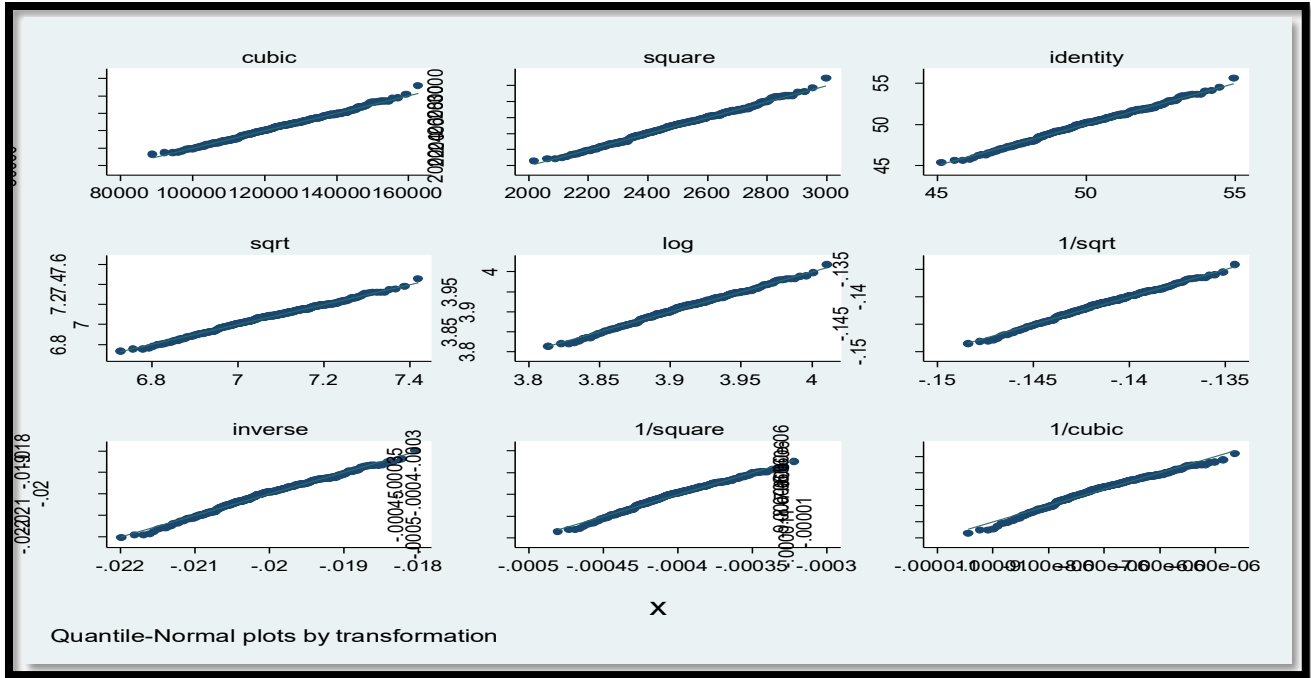


Fig. 4: Quantile plots of transformed data when n=250

Table 3: Normality tests on transformed data when n = 500 and n = 1000

Sample size	Transformation	Formula	chi2	Pr(chi2)	Swilk	Pr(Swilk)	Sfrancia	Pr(francia)
500	cubic	x^3	14.0500	0.0010	0.9896	0.0013	0.9891	0.0014
	square	x^2	7.4200	0.0240	0.9942	0.0555	0.9938	0.0395
	identity	x	2.5300	0.2820	0.9971	0.5331	0.9968	0.3624
	square root	\sqrt{x}	1.1400	0.5660	0.9979	0.8037	0.9975	0.6014
	log	$\log(x)$	0.5300	0.7660	0.9983	0.9013	0.9979	0.7189
	1/square root	$1/\sqrt{x}$	0.7400	0.6910	0.9982	0.8752	0.9978	0.6781
	inverse	$1/x$	1.7900	0.4090	0.9976	0.6988	0.9972	0.4854
	1/square	$1/(x^2)$	6.5000	0.0390	0.9952	0.1192	0.9947	0.0749
	1/cubic	$1/(x^3)$	13.4500	0.0010	0.9909	0.0035	0.9903	0.0030
1000	cubic	x^3	28.6300	0.0000	0.9899	0.0000	0.9898	0.0000
	square	x^2	14.5300	0.0010	0.9944	0.0010	0.9944	0.0013
	identity	x	5.1400	0.0760	0.9973	0.0887	0.9973	0.0831
	square root	\sqrt{x}	2.2300	0.3270	0.9980	0.2922	0.9980	0.2635
	log	$\log(x)$	0.9200	0.6330	0.9983	0.4573	0.9984	0.4141
	1/square root	$1/\sqrt{x}$	1.1300	0.5690	0.9982	0.3956	0.9983	0.3583
	inverse	$1/x$	2.8000	0.2470	0.9977	0.1785	0.9977	0.1642
	1/square	$1/(x^2)$	9.8400	0.0070	0.9954	0.0040	0.9954	0.0047
	1/cubic	$1/(x^3)$	20.1700	0.0000	0.9914	0.0000	0.9914	0.0000

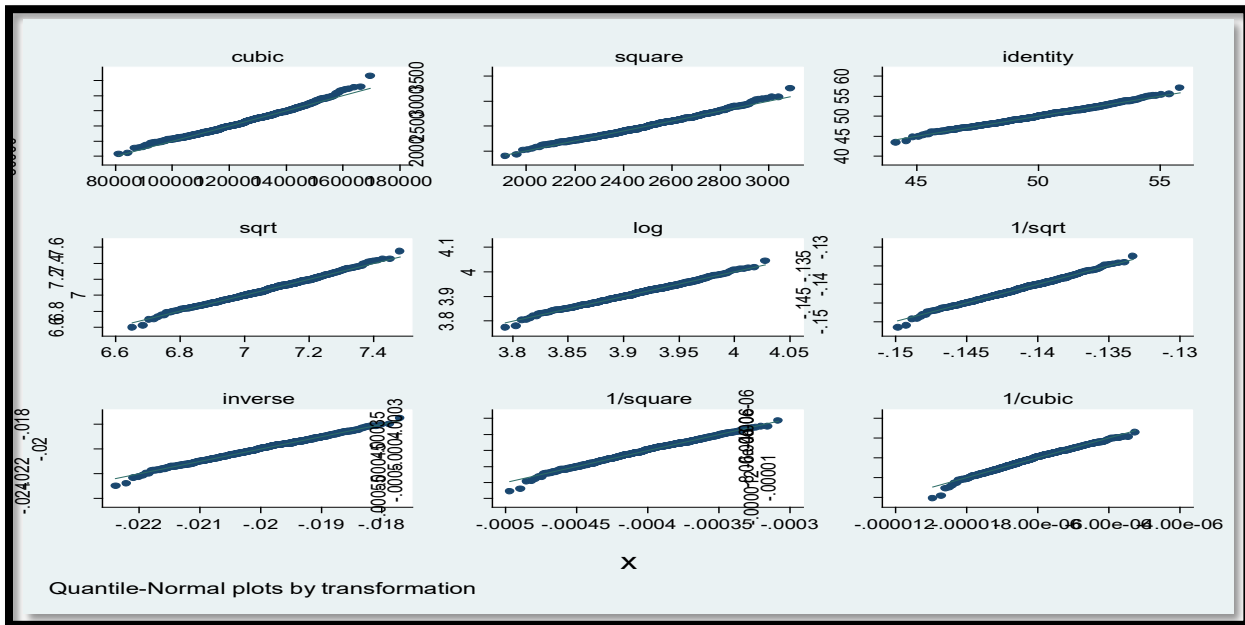


Fig. 5: Quantile plots of transformed data when n=500

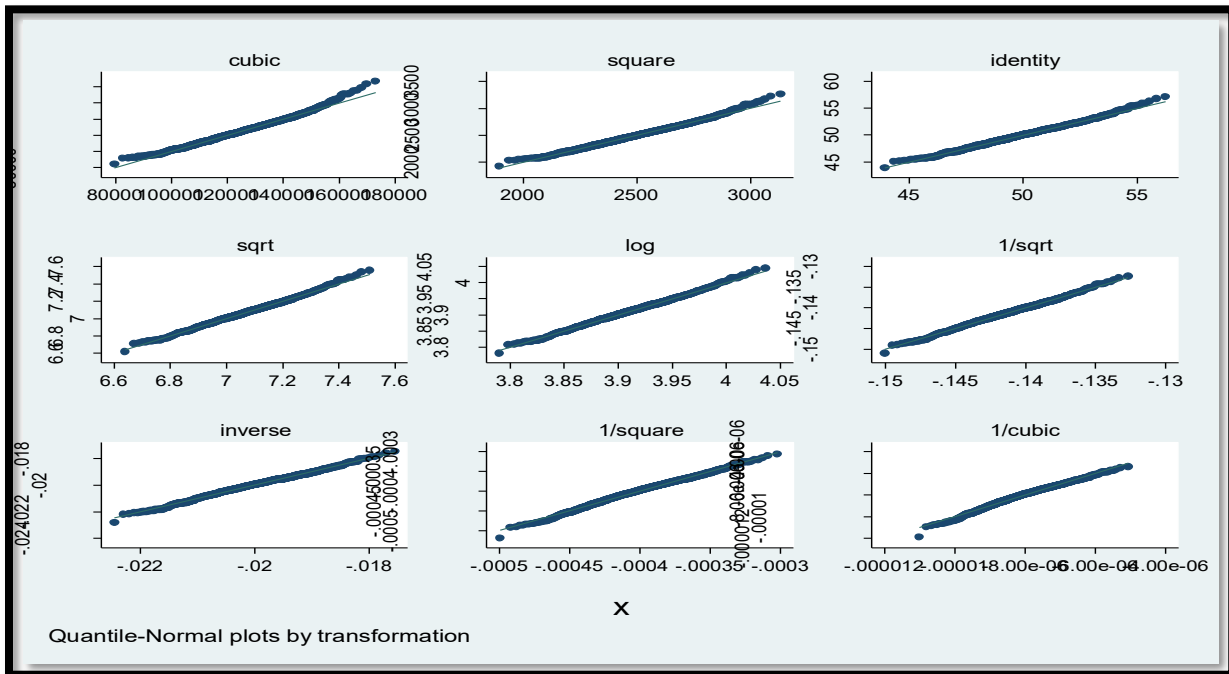


Fig. 6: Quantile plots of transformed data when n = 1000

5.0 Discussion of Results

It is discovered that normality increases as the sample sizes increase on the quantile plots. The transformed data is used to compare the normality with the introduction of Chi-square, Shapiro-wilk and Shapiro-Francia test statistics. It is also discovered that dispersion has effect on normality of the transformed data, the departure from normality increases as the measure of dispersion increases.

Comparison studies have concluded that order statistic correlation tests such as Shapiro–Francia and Shapiro–Wilk are among the most powerful of the established statistical tests for normality (Razali and Wah, 2011). One might assume that the covariance-adjusted weighting of different order statistics used by the Shapiro–Wilk test should make it slightly better, but in practice the Shapiro–Wilk and Shapiro–Francia variants are about equally good. In fact, the Shapiro–Francia variant actually exhibits more power to distinguish some alternative hypothesis (Ahmad and Khan, 2015).

6.0 Conclusion and Recommendation

Making valid conclusion on whether data is normally distributed or not is mostly needed by researchers across the globe, and this can be done using the plots and the classical tests carried out in this paper. Considering the plot obtained on the squared transformed data when $n = 1000$, visually, one may quickly say the data is normally distributed, but its corresponding p-values using the classical tests Chi-square, Shapiro-Wilk, and Shapiro-Francia are 0.0010, 0.0010, and 0.0012 which indicate rejection of normality assumption. Therefore, the quantile plots are most appropriate with few samples.

From the results obtained in this work, it can be concluded that sample sizes and measures of dispersion have significant effect on detection of normality in a set of data using the quantile plots. As Normality increases the sample sizes increase, but decreases as the standard deviation increases. It is therefore recommended that the quantile plot be employed only when the sample size is small. However the classical tests always give objective and precise results.

7.0 References

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Corresponding Email: isaacoluwaseviajao@gmail.com
awogbemiadeyeye@yahoo.com
urama.kenny@mouau.edu.ng