Data Screening and Preliminary Analysis on The Impact of Rural Infrastructure on Rice Productivity in Kano State, Nigeria

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Abstract

Despite having vast farmland suitable for paddy rice farming, local production in the country is weak, especially in Kano where the state has the most abundant farmland put to rice farming and the most extensive rice farmers in the 36 states of the country. As such, over 4mm/t of milled paddy rice has to be imported annually into Nigeria to supplement home production. The economy cannot sustain rice import because it depends on crude oil revenue; thus, leading to scarcity of rice at an exorbitant price. The study was conducted in the 2018 cropping season for rainfed and irrigated paddy rice, to identify the impact of rural infrastructure on the productivity of rice farmers in Kano State, Nigeria. There are seven local governments with 17 rice clusters in the state that are cultivating rice. A random sample of 768 rice farmers was selected in 9 rice clusters from the population of 135,895 rice farmers using multistage and purposive sampling. Using the Statistical Package for Social Science (SPSS) software version 22, data screening and preliminary analysis was conducted, aimed at satisfying the assumptions of the multivariate analysis. Thus, missing data analysis was performed to identify univariate outliers and multivariate outliers. Likewise, normality skewness and kurtosis, as well as multicollinearity issues, were checked. The preliminary analysis indicates that the data fulfil the conditions of multivariate analysis, thus, suitable for inferences.

Keywords: Rural Infrastructure, Preliminary Analysis, Data Screening, Kano State, Rice Farmers

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INTRODUCTION

In any multivariate analysis, data screening is an important aspect that lays the foundation of the results of a quantitative study. As such, it is imperative to identify any likely violation of the underlying assumptions of multivariate analysis through data screening (Hair Jr., Black, & Anderson, 2010). Therefore, the quality of the outcome of the study and acceptability depends on the data screening though; researchers mostly skip this stage of research due to its burden (Gorondutse & Hilman, 2014; Maiyaki & Moktar, 2011). The absence of data screening often leads to poor quality of the result and accuracy of the type of analysis used. Although Tabachnick and Fidell (2013) believed that the screening could be performed by proofreading of the original data generated from the computer file. However, proofreading may only apply to a small data set, but when the data is large, it is cumbersome to proofread the data on a computer. Thus, the need to examine the data using computer software for descriptive statistics, since the computer software exposes hidden errors that might not be discovered through proofreading (Hair Jr. et al., 2010).

Furthermore, data screening raises the awareness of the researcher on the interrelationship among the variables. Thus, it enables articulated result interpretation; fulfilling the assumptions of multivariate data analysis is achieved. Hence, as recommended by Hair Jr. et al. (2010), the study examined

issues concerning missing values, outliers, multicollinearity, and response bias.

LITERATURE REVIEW

Literature such as (Antle, 1984; Binswanger, Khandker, & Rosenzweig, 1993; Cook, 2011; Craig, Pardey, & Roseboom, 1997; Gajigo & Lukoma, 2011; Kiprono & Matsumoto, 2014; Llanto, 2012; Loksha & Mahesha, 2016; Lozano-Espitia & Ramirez-Villegas, 2016; Manjunath & Kannan, 2015; Narayanamoorthy & Hanjra, 2006; Teruel & Kuroda, 2005; Zhang & Fan, 2004) have shown that infrastructure has a significant impact on the farmers' productivity.

Road Networks

Billions of people worldwide were disconnected to the workplace, health care facilities, credit facilities, and educational opportunities due to the absence of road or high cost of transportation (Mikou, Rozenberg, Koks, Fox, & Peralta Quiros, 2019). Access to the all-season rural road network will significantly increase the welfare of rural farmers. Hence, rural roads network connects farmers with their farmlands, inputs, and outputs markets, as well as expanding farmers' accessibility to credits (Dercon, Gilligan, Hoddinott, & Woldehanna, 2009). Even though, Pavel and Moldovan (2019) reported that within short a period, there is an insignificant influence of roads network with local economic development.

Farm Size

The size of the farm affects output produced as reported by Akudugu (2016) and Tashikalma, Giroh, and Ugbeshe (2014) that the size of the farm significantly affects rice production. Also, Osanyinlusi and Adenegan (2016) indicate that farm size has a significant positive impact on the efficiency of rice production. Furthermore, Ragasa and Chapoto (2017) reported that out of the 7.5% increase in rice productivity, 6% is attributed to expansion in the land area. Also, Bhattacharyya and Mandal (2016) and Wang, Chen, Gupta, and Huang (2015) reported an increase in yield due to a growth in farm size and yield decreases with land fragmentation.

Yan, Chen, and Hu (2019) report an inverted-U shape correlation between farm size and output efficiency, and farm size and profit efficiency in agricultural production in China, and Sheng, Ding, and Huang (2019) shows an inverse relationship between farm size and productivity in most small size farms. Further, the choice of labour or capital intensive may smooth the non-linearity of farm size and productivity relationship. At large scale production, it is more likely that capital intensive will affect the relationship between farm size and productivity. Thus, preparing farmers to be capital intensive is better than subsidizing rent to acquire more land with labour-intensive.

Similarly, Zhong, Zhu, Chen, Liu, and Cai (2019) obtained an inverted U-shaped relationship between farm size and technical efficiency for farmers that combined farming with other business. Moreover, the farm size technical efficiency increases with the level of engagement in other enterprises. Further, the variation in technical efficiency of involvement depends on the farm size. Hence, eliminating technical inefficiency will increase crop yield by 12%. Also, the result of a study by Ren et al. (2019) shows an increase in farm size has a positive effect on the net profit of a farmer, economic, technical, and labour efficiency.

Furthermore, an increase in farm size significantly reduces the use of fertilizer and pesticides. Expansion in large-scale farming is a step forward to revolutionizing agricultural practices. Also, to attain food security in a country even though there is a poor understanding of allocative efficiency, which requires further research.

Irrigation Facilities

A study by Gajic, Kresovic, Tapanarova, Zivotic, and Todorovic (2018) shows in the semi-dry and dry period; a quadratic relationship exists between yield and watering. Thus, irrigation becomes necessary for semi-dry and dry periods. Therefore, the availability and utilization of irrigation facility would increase rice yield (Ahmed, Xu, Yu, & Wang, 2017). Similarly, Chun et al. (2016) report an improvement in irrigation facilities led to an increase in rice yield from 8.2% to 42.7%. This is because expansion in irrigated land increases rice productivity (Ragasa & Chapoto, 2017). However, the scarcity of water causes a severe loss to world crop and is expected to worsen. It was reported by Comas, Trout, DeJonge, Zhang, and Gleason (2019) that water stress led to a decline in yield but can be revegetated through irrigation. This led to the development of some-water saving management practices in areas where agriculture depends on irrigation, to increase yield.

Maneepitak et al. (2019) reported that the alternate wetting and drying increases crop yield by 15% during the wet season, 7% in the dry season, and yield more output compared to continuous flooding. It further reduces water input by 19% in the wet season and 39% during the dry season, leading to an improvement in the productivity

of water by 46% during the wet season and 77% in the dry season. Though the study by Yamaguchi, Tuan, Minamikawa, and Yokoyama (2019) shows, farmers are in favour of continuous flooding.

Electricity Supply

Electrifying rural areas will promote productive activities in the region by reducing the cost of maintenance and back up. While the inadequate amount of electricity in the rural areas distorts productive activities of the rural people (Narula & Bhattacharyya, 2017). Barnes and Binswanger (1986) reported that private rural electrification significantly affects agricultural productivity. Though Li, Chen, and Liu (2019) reported that individual energy is expensive, therefore cannot be accessed by rural dwellers. Also, electrifying pumps increase investment in irrigation by 28% and output by 2% (Binswanger et al., 1993) while, subsidy removal in electricity causes food inflation (R. Bhattacharyya & Ganguly, 2017). Thus, Langarita, Chóliz, Sarasa, Duarte, and Jiménez (2015) advocate for a low tariff on electricity to the rural dwellers.

Communication Network

Communication is a vital tool for farmers as reported by Elly and Silayo (2013) that farmers are using traditional interface to source data on agriculture. The modern communication system bridges the gap in the data anomalies, reduces the gap in accessing and conveying inputs and outputs. For instance, mobile phones nowadays ease the adoption of technology through information and computer technology agricultural extension programs. It was reported by Kirui, Okello, Nyikal, and Njiraini (2013) that the services of MMT increase commercial agriculture by 37% annually.

Khanna and Kaur (2019) reported that internet of thing has a significant impact on modern agriculture. The internet of thing enables farmers to regulate the management of agricultural activities using remote sensing effectively. Further, the internet of thing minimizing human effort, saving time, increasing yield and profit. The media preference of farmers is motivating and engaging media like practical demonstration or television, then mobile phones due to its convenience, and books for details (Moyo & Salawu, 2019).

Fertilizer Access

The expedient modern means of increasing the productivity of crop is enhancing micronutrient (Tiwasing, Dawson, & Garrod, 2019). Tashikalma et al. (2014) and Zhu and Chen (2002) reported that chemical fertilizer positively affects crop production. Also, Stewart, Dibb, Johnston, and Smyth (2005) report that the nutrients of fertilizer upsurge crop yield from 30% to 50%. Furthermore, fertilizer usage seasonally increases crop return by 35% and annually by 69% (Duflo, Kremer, & Robinson, 2008).

Also, Zhang et al. (2017) reported that nitrogen significantly increases the growth rate of crop and rice yield. Similarly, a study by Osanyinlusi and Adenegan (2016) and Mandal, Patra, Singh, Swarup, and Masto (2007) shows that the usage and quantity used of fertilizer positively affect the productivity of farmers. Moreover, a comparative study result shows a further increase in rice yield can be attained using fertilizer in Hainan, China and Niger, Nigeria (Ahmed et al., 2017). Thus, Ajani and Ugwu (2008) recommend supplying fertilizer in the right place and time.

Access to Credit

Access to formal and informal credit facilities have a positive and significant impact on agricultural production (Akudugu, 2016; Nan, Gao, & Zhou, 2019). Insufficient finance becomes a key obstacle to rice productivity Ojochenemi, Gabriel, and Ogwuche (2017), and a significant setback to modern technology adoption (Hena, Jingdong, Zhang, Memon, & Khalil, 2019). Besides, a study by Hena et al. (2019) and

Nonvide, Sarpong, Kwadzo, Anim-Somuah, and Gero (2017) shows access to adequate credit facility increases the productivity of farmers, eases proper utilization of inputs, permits new technology adoption, and provides an opportunity for enhancing technical skills.

Moreover, Binswanger et al. (1993) reported that the fast growth of banks, resulted to an increase in fertilizer demand by 23%, raised pumps investment by 41%, raised tractor investment by 13%, and upsurged crop harvest by 3%. Unfortunately, most banks shine away from rural banking due to the enormous risks involved. Ijaiya, Abdulraheem, and Abdullahi (2017) opined that banks shine away businesses which involve considerable uncertainties, particularly in the rural areas. Thus, financial institutions prefer business in the regions that have excellent infrastructure with relatively fewer risks in agriculture (Binswanger et al., 1993).

Nyaga and Nzulwa (2017) indicated that the inability of farmers to access credit is due to poor awareness and the managerial skills required by the farmers. Also, Islam and Siwar (2012) reported that systematized farmers have more access to formal funding than un-organized farmers. Similarly, a study by Roberts, Otieno, and Nyikal (2017) shows that farmers with bank account have more access to a formal credit facility compared to those without a bank account and that, a significant negative correlation exists between access to credit and literacy, profession, and group membership. Abdallah, Ayamga, and Awuni (2019) indicates gender, age, literacy, farm size, labour, wealth and group membership significantly determine credit access, and Bai, Shi, Liu, and Sarkis (2019) opined creditworthiness depends on education and skills of the farmer.

Access to Market

An improvement in accessing market by the rural farmers increases crop productivity (Koppmair, Kassie, & Qaim, 2016). Bohl and Sulewski (2019) reported that the short-long term activities of speculators under scrutiny lessen the volatility rate in the markets. Further, Kaminski and Christiaensen (2014) report that market facilities reduced the risk related to post-harvest losses. Hence, access to the market by rural farmers facilitate an increase in agricultural productivity. Therefore, Uduma, Samson, and Mure (2016) emphasized in having a supportive market in rural areas. Czyzewski and Majchrzak (2017) and Goto and Douangneune (2017) suggest government intervention to support rural markets.

Similarly, Binswanger et al. (1993) maintained that controlled markets led to a growth rate of 87%, contributes 4% to agricultural output, and 17% to the demand for fertilizer, lift farmers liquidity position, and cut down the costs of business for banks and farmers. Further, Uduma et al. (2016) opined that weak supportive market in the rural areas is a constraint to increasing rice productivity though Akudugu (2016) reported that access to a market is not significantly correlated to agricultural productivity.

Access to Extension Services

The term extensions refer to the services offered by extension workers to farmers on ways of increasing crop productivity (Antle, Zhang, Mu, Abatzoglou, & Stöckle, 2018; Golan & Kohli, 2013). Also, extensions can be practical through contact with farmers or by publications or by radio programs. The latter is preferred due to its broader coverage and in the physical absence of extension agent (Adekunle et al., 2004). A study by Binam, Tonyè, Wandji, Nyambi, and Akoa (2004) shows an increase in groundnut returns of 77%, maize 73%, and cropping maize and groundnut 75% as a result of extensions offered to farmers. Also, Dercon et al. (2009) report that one extension visits led to a reduction of poverty by 9.8%

and upsurge consumption by 7.1%. Owens, Hoddinott, and Kinsey (2003) report one to two extension visits led to a rise in crop yield by 15%.

Furthermore, a study by Alene and Manyong (2007), Jin, Huang, Hu, and Rozelle (2002), Maffioli, Ubfal, Vazquez-Bare, and Cerdan-Infantes (2013), and Pender and Gebremedhin (2007) shows a significant impact of extensions on modern agriculture adaptations. So, Berhanu and Poulton (2014) opined that an efficient program of increasing farmers productivity is an investment in extensions as Jin and Huffman (2016) reported a high return on investment in extensions. Therefore, Garnett et al. (2013) stressed extension services to back an increase in farmers productivity. Birkhaeuser and Evenson (1991) affirmed that most research results on extension investment show a return of more than 40%. Thus, concludes that estimates were consistent, extension services increase agricultural productivity. Though farmers negatively perceived agricultural extension services (Al-Zahrani, Khan, Baig, Mubushar, & Herab, 2019).

3 METHODOLOGY

In assessing the data for this study, the descriptive and inferential statistics were carried out using the SPSS version 22 software. Consequently, Mahalanobis distance and correlation analysis were performed. The sample for the study was collected from the rice farmers in the 17 rice clusters of the 7 local governments of Kano state that are cultivating paddy rice. The multistage sampling technique was used to select the local governments for the study — further a random selection of 768 rice farmers from a population of 135, 685 in 9 rice clusters. A total of 656 usable questionnaires were retrieved from the 9 rice clusters.

RESULTS AND DISCUSSION

This segment presents the result and discussion of the data collected for the study.

Descriptive Statistics of the Respondents

Table 1 present the summary of sex, age qualification, marital status, and experience of the respondents in the study area. From Table 1, there are 131 female rice farmers and 525 male rice farmers, indicating there are more male rice farmers than female rice farmers. The age group of the respondents shows that farmers who are below the age of 20 years rice farmers are 84, 20-29 years are 134, 30-39 years are 212, 40-49 years are 151, and 50 and above years are 151. This shows that 55.5% of the rice farmers are within the working population group age bracket 30-49 years, with a prospect for young farmers age bracket below 20-29 years of 33.2%. Also, 23.9 % of the respondents have at least a primary certificate, but 59.4% have secondary and above education. Further, the Table shows that 73.9% of the respondents are married, and 77.6% have more than 5 years of rice farming experience.

Response Rate

The number of questionnaires distributed was 768 in the 9 rice clusters, out of which 739 were returned representing 96.22%. However, the usable questionnaires were 656 as 83 were deleted in the process of data cleaning, representing a reasonable response rate of 85.42%. Further, the response rate from each rice cluster is reasonable, ranging from 78.67% to 88%, with no cluster having a poor response rate.

Test of Non-Response Bias

The non-response bias in a survey refers to the failure to get the required information from the respondents, which can affect the findings of the study. Hence, the need to assess such

error before continuing with the analysis. No below minimum bias response rate nor maximum, which a study estimate is inevitably biased (Singer, 2006). In addressing this problem, 100% was added to the computed sample as recommended by Salkind (1997).

Table 1. Summary of Respondents' Demography

S/No.	Items	Frequency	Percentage
1	Sex		
	Female	131	20
	Male	525	80
2	Age		
	Below 20 years	84	12.8
	20-29 years	134	20.4
	30-39 years	212	32.3
	40-49 years	151	23.0
	50 and above years	75	11.4
3	Qualification		
	No formal education	109	16.6
	Primary education	157	23.9
	Secondary education	212	32.3
	Tertiary education	178	27.1
4	Marital status		
	Single	171	26.1
	Married	485	73.9
5	Experience		
	1-5 years	147	22.4
	6-10 years	230	35.1
	11 and above years	270	42.5

Table 2. Response Rate of the Questionnaires

Cluster	Questionnaire						
	Distributed	Returned	Returned And Usable	Returned But Excluded	Unreturned	% Response Rate	%Usable Response Rate
Lautaye	75	70	66	4	5	93.33	88
Dokasati	75	72	66	6	3	96	88
GarinAli	80	75	69	6	5	93.75	86.25
Kadawa	80	77	66	11	3	96.25	82.5
Bugau	75	73	59	14	2	97.33	78.67
Karfi	100	96	88	8	4	96	88
Kura	90	88	78	10	2	97.78	86.67
Nata'ala	75	73	64	9	2	97.33	85.33
Larabar	118	115	100	15	3	97.46	84.75
G/Sarki							
9clusters	768	739	656	83	29	96.22	85.42

Further, extension workers, research assistants were used with some inducements, followed by phone calls and text messages, in motivating rice farmers to participate, so that the required information can be obtained (Churchill & Iacobucii, 2004). The likely variance among the early and late response was compared using the entire study variables. The returned questionnaires were recorded based on early and late responses, and an independent T-test was carried out to ascertain the existence of differences between the two groups, as presented in Table 3 and Table 4 below.

The result of Table 3 shows no stern difference in the group mean and standard deviation for the early response and late response, except the response on farm size, irrigation, and communication. The 2-tail t-test result Table 4 shows that there is no significant disparity with respect to the early and late respondents based on Road networks ($t = -0.064$, $p < 0.949$), electricity supply ($t = 0.103$, $p < 0.918$), access to fertilizer ($t = 1.252$, $p < 0.211$), access to market ($t = 0.174$, $p < 0.862$), access to credit ($t = 0.478$, $p < 0.633$), and access to extension services ($t = 1.445$, $p < 0.149$). While, Farm size ($t = 3.971$, $p < 0.000$), irrigation facilities ($t = 5.606$, $p < 0.000$), and communication networks (t

$t = 5.214$, $p < 0.000$) shows a disparity between the early and late respondents. So, based on the tests result in Tables 3 and Table 4 (Appendix -A), a conclusion can be drawn that there is no problem of response bias

Table 3. Group Descriptive Statistics for Early and Late Respondents

	Group	N	Mean	Std. Deviation	Std. Error Mean
Rdn	Early	485	4.0572	.66839	.03035
	Late	171	4.0614	.90904	.06952
Fsz	Early	485	4.4532	.51633	.02345
	Late	171	4.1888	.81475	.06231
Irg	Early	485	4.0716	.75130	.03411
	Late	171	3.5629	1.09983	.08411
Etr	Early	485	3.3795	.98211	.04460
	Late	171	3.3699	1.23828	.09469
Com	Early	485	4.4620	.53215	.02416
	Late	171	4.0629	.94988	.07264
Ftz	Early	485	3.3588	.45044	.02045
	Late	171	3.4196	.75569	.05779
Mkt	Early	485	3.2660	.72676	.03300
	Late	171	3.2535	.99926	.07642
Crd	Early	485	2.9190	.77713	.03529
	Late	171	2.8837	.96563	.07384
Ext	Early	485	2.8146	.91842	.04170
	Late	171	2.9368	1.03998	.07953

Data Examination, Screening and Preparation

The screening, editing, and preparation are vital steps to be taken before multivariate analysis to identify whether the underlying assumptions of multivariate were violated (Hair Jr et al., 2010). Further, the data examination allows the researcher to have a deep sympathetic of the data obtained; hence, missing data, outliers, normality, and multicollinearity were checked and treated accordingly.

Analysis of Missing Data

Given the effect of missing data in the analysis, a protective strategy was used by the researcher at the collection point to reduce the rate of missing data. On the receipt of the returned completed questionnaire, the extension workers, research assistants, and researcher often checked to ensure proper filling of all the questions. Where an item(s) was not filled, politely the attention of the respondent is drawn to complete it (Maiyaki & Moktar, 2011). Though Hair Jr. et al. (2010) recommends replacement of missing values using mean when it is less than 5% per item. Thus, the missing value analysis in this study showed one case of missing values of 2 and was treated in SPSS version 22, using the SMEANS.

Analysis of Outliers

Another vital segment of data screening in a survey study is the assessment of outliers. An outlier is an extreme score that can alter the outcomes of a result (Maiyaki & Moktar, 2011). The outlier can have a higher or lower value compared to remaining scores in a question, thereby making the examination stance out from the remaining (Hair Jr. et al., 2010). The multivariate analysis may confirm the detection and handling of outliers. In this regards, univariate and multivariate analysis was conducted to detect the outliers. The univariate outliers were checked using the SPSS by detecting cases with large z-score values exceeding 3.29 which are considered as potential univariate outliers, and such response was deleted from the analysis (Tabachnick & Fidell, 2013).

Furthermore, the Mahalanobis Distance (D) was conducted to discover and deal with multivariate outliers (Hair Jr. et al., 2010). Thus, Mahalanobis test was conducted in SPSS and compared with the Chi-square table (Tabachnick & Fidell,

2013). The items adapted were 41, representing 40 degrees of freedom in the X2 table with $P < 0.001$; the standard is 73.402 (Tabachnick & Fidell, 2013). This infers that any figure with a Mahalanobis Distance of 73.402 and higher is a multivariate outlier thus should be deleted. As such, no cases were established to be 73.402 and above, implying no multivariate outliers.

Normality Test

Normality of the data collected for the study was checked. Normality test is a significant supposition in a multivariate analysis that pacts with the flora of data flow for an individual construct and its association to a normal distribution (Hair Jr. et al., 2010; Tabachnick & Fidell, 2013). In checking the normality of the data, skewness and kurtosis statistics was used (Hair et al., 2010). Though, when the sample for the study is greater than 200 like the present study with 768 samples, the deviation from the normality of skewness and kurtosis sometimes may not show a substantive difference in the analysis (Tabachnick & Fidell, 2013). Moreover, Kline (2011) argued that the absolute value of skewness that is more than 3 and kurtosis value greater than 10 might signify a problem and values greater than 20 can infer a more severe problem. The preliminary test of normality conducted for all the items used in the study shows that the absolute value for skewness is 2 and kurtosis is 6.29, signifying both are within the accepted range of <3 and <10 respectively.

Multicollinearity Test

Multicollinearity is the relationship between two or more variables, and it becomes a problem when the variables relate to one another as high as 0.9 or more (Pallant, 2007; Tabachnick & Fidell, 2013). This means that the highly correlated variables contain needless information that needs to be reduced, as not all are required for the analysis because they increase the size of the error term and the standard error of the regression coefficient. Thus, the statistical significance of the coefficients becomes weak. Therefore, Hair Jr. et al. (2010) and Pallant (2007) recommends the use of tolerance and Variance Inflation Factor (VIF) in examining multicollinearity problem with cut-off points of more than 0.1 and not exceeding 10 respectively. The result from Table 5 shows that the tolerance values range from 0.609-0.876 significantly higher than 0.10. Also, the VIF ranges between 1.141-1.643, which is less than 10, thus concluded that the problem of multicollinearity does not exist among the exogenous variables.

Table 5. Multicollinearity Test Based on Tolerance and VIF

Exogenous Variables	Tolerance	VIF
Road Networks	.790	1.266
Farm Size	.703	1.423
Irrigation Facilities	.788	1.269
Electricity Supply	.661	1.513
Communication Network	.870	1.150
Fertilizer Access	.876	1.141
Credit Access	.757	1.322
Market Access	.637	1.570
Extension Services	.609	1.643

Furthermore, to re-affirm the absence of multicollinearity among the exogenous variables, Pearson's correlation was calculated using the SPSS as presented in Table 6. The scale is that any relationship between variables of 0.9 and above is considered as a problem. Hence, from Table 6 (Appendix - A), the values of the variables range between 0.006-0.420 far below the yardstick, therefore, conclude there is no multicollinearity problem among the variables for this study (Hair Jr. et al., 2010).

CONCLUSION

The paper examines the data collected using statistical methods to certify the fulfilment of the multivariate assumptions. Though the data presents a small number of missing values which is less than 5%, and are treating under value replacement (Hair, Jr. et al., 2010), using SPSS. Hair (2010) and Tabachnick and Fidell (2013) suggest removing univariate and multivariate from data. Therefore, the identified univariate and multivariate were deleted. Hence, the data is ascertained as normally distributed with no response bias. The screened and cleaned data for the study is now furnished for multivariable analysis.

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Appendix –A

Table 4. Independent samples T-test for equality of means Leven Test for equality of variance

		F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95 Conf. of The Lower	Interval Difference Upper
Rdn	Equal variance (Assumed)	19.094	.000	-.064	654	.949	-.00419	.06568	.13316	.12479
	Equal variance (Not assumed)			.055	237.948	.956	-.00419	.07585	-.15362	.14524
Fsz	Equal variance (Assumed)	74.029	.000	4.887	654	.000	.26434	.05409	.15814	.37055

		F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95 Conf. of The Lower	Interval Difference Upper
Irg	Equal variance (Not assumed)			3.971	220.003	.000	.26434	.06657	.13315	.39554
	Equal variance (Assumed)	50.499	.000	6.686	654	.000	.50878	.07610	.35935	.65821
Etr	Equal variance (Not assumed)			5.606	228.369	.000	.50878	.09076	.32995	.68762
	Equal variance (Assumed)	25.580	.000	.103	654	.918	.00964	.09380	-.17455	.19383
Com	Equal variance (Not assumed)			.092	249.459	.927	.00964	.10467	-.19651	.21579
	Equal variance (Assumed)	92.244	.000	6.735	654	.000	.39916	.05927	.28277	.51554
Ftz	Equal variance (Not assumed)			5.214	208.808	.000	.39916	.07655	.24824	.55007
	Equal variance (Assumed)	69.462	.000	-1.252	654	.211	-.06083	.04860	-.15626	.03460
Mkt	Equal variance (Not assumed)			-.992	214.078	.322	-.06083	.06130	-.18166	.06000
	Equal variance (Assumed)	35.276	.000	.174	654	.862	.01247	.07173	-.12837	.15332
Crd	Equal variance (Not assumed)			.150	236.435	.881	.01247	.08324	-.15151	.17645
	Equal variance (Assumed)	14.034	.000	.478	654	.633	.03531	.07384	-.10969	.18030
Ext	Equal variance (Not assumed)			.431	251.894	.667	.03531	.08184	-.12588	.19649
	Equal variance (Assumed)	6.626	.010	-1.445	654	.149	-.12229	.08462	-.28845	.04388
	Equal variance (Not assumed)			-1.362	269.195	.174	-.12229	.08980	-.29909	.05451

Table 6. Correlations among the exogenous variables

	Rdn	Fsz	Irg	Etr	Com	Ftz	Crd	Mkt	Ext
Rdn	1								
Fsz	0.404	1							
Irg	-0.006	0.283	1						
Etr	0.369	0.332	0.020	1					
Com	0.253	0.351	0.093	0.405	1				
Ftz	0.043	0.094	0.083	0.142	0.188	1			
Crd	0.061	0.137	0.321	-0.094	0.079	0.169	1		
Mkt	0.017	.0165	0.246	-0.237	0.083	0.227	0.419	1	
Ext	-0.132	0.054	0.346	-0.244	0.031	0.188	0.401	0.420	1