Logit, Probit and Tobit Models in Modeling Consumers' Willingness to Pay for Electricity Bill in Port Harcourt City Local Government Area of Rivers State

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Abstract

An outstanding problem for the service providers of Electricity in Port Harcourt City Local Government area of Rivers State and most cities of Nigeria is the unwillingness to pay the prescribed bills by the consumers. The unwillingness to pay can be traced to unrealistic electricity bill from the service provider to consumers as well as the influence of demographic and socioeconomic factors on the side of consumers. This study identifies how the demographic and socioeconomic factors influences consumers' willingness to pay electricity bill. Logit, probit and tobit models were used in modelling out consumers' willingness to pay electricity bill with the aid of stata software version 16, having the demographic and socioeconomic factors as the independent variables. The study also provided quantitative evidence of the correlation between the demographic, socioeconomic factors and consumers' willingness to pay electricity bill. Research questionnaires with a sample size of 1338 was adopted as the source of data for the study. The results show that there is positive correlation between consumers' willingness to pay for electricity bill, demographic and socio-economic factors in Port Harcourt City Local Government Area of Rivers State. The correlation coefficient of Consumers' willingness to pay with respect to the demographic and socioeconomic factors are 0.1828 and 0.1001 respectively while the correlation coefficient of the demographic factor with respect to the socioeconomics factor is 0.1755. The results of the Probit, logit and Tobit models were compared on the basis of Akaike Information Criterion (AIC) and Bayesian Information criterion (BIC) and it was found that the probit model with AIC and BIC values of 952.404 and -30.771 respectively was the best fitted model in modelling Consumers' willingness to pay for electricity bill in Port Harcourt City Local Government Area of Rivers State. The coefficients of the probit model associated with the demographic and socioeconomic factors that influences consumers' willingness to pay for electricity bill in Port Harcourt City Local Government Area are 0.5676279 and 0.3529775 respectively. These figures represent 56.7% and 35.3% increase in the Consumers' willingness to pay for a unit increase in the demographic and socioeconomic factors. The probit model and the associated confidents from this study offers a useful guide to the electricity service providers to arrive at an acceptable electricity bill to electricity consumers in Port Harcourt City Local Government Area of Rivers state.

Keywords: *Logit, Probit and Tobit Models in Modeling Consumers, Willingness, Electricity*

1.1 Background to the study

It is a well-known fact that one of the challenges confronting Nigeria economy is the issue of erratic power supply. Some sees it as the bane of economic and industrial development. Despite the facts that the country is blessed with abundant human and natural resources, it becomes paradoxical that after one hundred years of existence and sixty-one years of independence, Nigeria is still not getting it right in terms of energy sufficiency. If the problem is only that the power is insufficient, it would have been a much more bearable situation but the major problem is that the power supply is erratic. Being erratic mean that the residents and companies requiring electricity cannot predict when this electric power from the national grid will be available for their consumption. In most situations erratic power supply can be equated to no power supply as the work the power is needed for, might have been done before the supply is made available or the power is interrupted before what it is to be used for, is gotten ready. Erratic power supply can also be equated to negative power in situations where the flip-flop nature of the supply causes damage to the equipment being powered. In a bid to fathom the actual causes of erratic power supply, researchers have attributed to several factors among which are consumers' unwillingness to pay to avoid power outages (Ju-Hee *et al.*, 2019), incompetent staff of the energy companies (Ohajianya1 *et al.*, 2014), government policy (Oyem, 2013), inefficiency in power generation, transmission, distribution and consumption (Ubi *et al.*, 2012), socioeconomic and demographic factors (Oyem, 2003).

According to the International Energy Agency report (2012), electric power transmission and distribution losses in Nigeria stood at 17.22% in 2010, and the maximum figure between 1971 and 2010 occurred in year 1981 where the loss stood at 49.27%. Ju-Hee *et al.,* (2019), further explained that the typical Nigerian firm experiences power failure or voltage fluctuations about seven times per week, each lasting for about two hours, without the benefit of prior warning. This imposes a huge cost on the firm arising from idle workers, spoiled materials, lost output, damaged equipment and restart costs. The overall impact is to increase business uncertainty and lower returns on investment.

In 1990, the World Bank estimated the economic loss to the country from National Electric Power Authority (NEPA), a body now known as Power Holding Company of Nigeria PHCN; inefficiency at about N1billion. There are essentially five ways by which firms may respond to unreliable electricity supply. These are choice of location, factor substitution, private provision, choice of business and output reduction. While all these elements are presently observed among Nigerian firms, the most common approach has been through private provision. Electricity consumers have responded to PHCN inefficiency through self-generation. Electricity users, both firms and households, now find it necessary to provide their own electricity in part or in whole to substitute or complement PHCN supply by factoring generator costs into the overall investment cost, thus raising significantly the set-up cost for manufacturing firms operating in the country.
One implication of the existing electricity market structure is that PHCN, by taking advantage of the huge economies of scale in the industry, is able to supply electricity at much lower cost than private provision. This cost differential is large, sometimes running to over four

times(Ukoko, Odogwu, & Adenusi ,2014). A 1983 joint UNDP/World Bank study estimated a cost differential of 16–30% for large industrial establishments in the country with auto-generation. In spite of this large cost differential, however, over 90% of Nigerian manufacturers make provision for auto-generation. The relevant question then is, why are manufacturers willing to incur such a huge extra cost for self-generation? Is it possible that the manufacturers are perfectly rational agents who are willing to incur the extra cost of auto-generation as an insurance against the larger costs from power outage? An understanding of the behaviour of the firm is important in proffering policy recommendations to solve their energy problems. In addition, an analysis of outage costs may provide useful data for measuring the willingness of consumers to pay for reliable electricity supply, measure the inefficiency of PHCN and hence form a basis for reform of the public monopoly(Ukoko, Odogwu, & Adenusi,2014).

Also, investments in the use of generators may then be attributed to impute the costs incurred due to power outages. In addition, the study also investigates demographic and socioeconomic factors underlying the behaviours of consumers in the attempt to mitigate outage losses. The results of the analysis of demographic and socioeconomic factors will complement the revealed preference from the methodology with those obtained from survey and subjective valuation. The survey technique enables us to measure the impact of outage characteristics on outage costs. In terms of scope of coverage, the study focuses on the statistical analysis of Consumer's Willingness to Pay for Electricity Supply (Wertenbroch & Skiera, 2002).

Few studies have tried to measure the cost of electric power shortages in Nigeria and they include Ukpong (1973), Iyanda (1982), Lee and Anas (1992), Uchendu, (1993). This study is different from these studies in three important aspects the location, methodology and scope. The methodology combines the benefits of the revealed preference and survey techniques. The principle of revealed preference implies on the consumers' willingness to pay which may have inferred from the actions taken by consumers to mitigate losses induced by unsupplied electricity. This enables the study to use Probit, Logit and Tobit Models in Modelling Consumers' Willingness to Pay for Electricity Bill in Port Harcourt City Local Government Area of Rivers State. This is done with the target to determine whether there is any correlation between demographic, socio-economic factors and consumer willingness to pay, to Model consumer willingness to pay for electricity bill, determine best fitted model in modeling consumer willingness to pay for electricity bill and investigates coefficient of the model associated with demographic and socio-economic factors that influenced consumer willingness to pay for electricity bill in Port Harcourt City Local Government Area of Rivers State.

METHODOLOGY

3.1 Research Design

The study adopted a descriptive research design. This type of research design is appropriate in describing the characteristics of the variables without any intentions to manipulate them. According to Nwankwo (2013) descriptive survey design puts the researcher at a point where data generated from sample drawn from a given population describes certain features of the sample as they are at the time of the study without manipulating the variables.

3.2 Population of the Study

The population of the study limited to 26,760 electricity consumers within Port Harcourt City Local Government Area of Rivers State (Power Distribution Company Data Base, 2021).

3.3 Sample and Sampling Technique

The sample size of the study is 1338 and this was determine using percentage distribution (see Appendix for more details). According to Zahid and Raizwana (2012) the best method of determining sample size is to use 5percent of the population. The study involved the use of systematic sampling to obtain the required households. In this context, every sixth household will be interviewed. A total number of 1338 households will be sampled using a well-structured questionnaire. The information obtained was on the demographic and socio-economic characteristics and the willingness to pay for improved electricity supply.

3.4 Instrument for Data Collection

The instrument of the study is a self-designed questionnaire tagged "Application of Probit, Logit and Tobit Models on Household Survey Data". The questionnaire is divided into three sections, namely: section "A" which is concerned with the demographic characteristics of respondents, section "B" is composed of the questionnaire on consumers' Willingness to pay for electricity supply in Port Harcourt City Local Government Area of Rivers State and section "C" is composed of questionnaire on socioeconomic factors that influence consumers' willingness to pay for electricity supply in Port Harcourt City Local Government Area of Rivers State.

Table 3.1: Description of Variables to be Estimated in the Model

Explanatory Variables	**Description of the Variables under Investigation**	**Hypothesized Relationship with the Willingness To Pay (WTP) for Improved Electricity Supply**
Age (X_1)	Age of the respondents in years	Negative
Education (X_2)	Educational level of the respondents (no of years spent in school)	Positive
Marital status(X_3)	Marital status (D =1 if married, 0 otherwise)	Negative
Household size(X_4)	Number of people in the household	Negative
Occupation (X_5)	Occupation of the respondents (D = 1 if formal, 0 otherwise)	Negative
Source of Electricity (X_6)	Source of electricity used by the respondents (D = 1 if SWC, 0 otherwise)	Positive
Perception of the respondent towards the administration of the electricity utility (X_7)	Perception of respondents on who to provide electricity (D = 1 if government, 0 otherwise)	Negative
Time of electricity availability	Supply pattern (D = 1 if supplied	Positive

(X_8)	once in a week, 0 otherwise)	
Price (X_9)	Price household WTP for improved electricity supply (₦)	Negative
Monthly expenditure (X_{10})	Household monthly expenditure (₦) of food and nonfood items.	Positive

Monthly expenditure was used as a proxy for income as people cannot spend more than what they earned and because people do not disclose the real value of their monthly income.

3.5 Reliability of the Instrument

The instruments were administered to 29 electricity consumers who will not be part of this study, in order to establish the consistency of the test items. The Cronbach's Alpha statistics was used to analyze the data collected from the respondents; the Cronbach alpha is suitable because it measures internal consistency between items when the instrument is dichotomous in nature. The reliability coefficients of the instruments were established at 0.86 (see Appendix for details)

3.6 Formulation of the Logistic Regression Model

A logistic regression model is a regression model in which the dependent variable is binary in nature (having two categories). Independent variables can be continuous or binary.
The linear regression becomes unsuitable for modeling the binary response variable because of the violation of the following assumptions:

i. Normally distributed Errors
ii. Homoscedasticity assumption is violated.

The dependent variable Y_i may follows binomial distribution and not normal. If the outcome Y_i is binary, taken on values either 0 or 1, the response variable Y_i is a Bernoulli random variable with probability distribution as shown below.

Y_i	P(Y)
1	α_i
0	$1-\alpha_i$

The expected response is given as follows:

$$E(Y_i) = 1.\alpha_i + 0.(1-\alpha_i) = \alpha_i \quad (3.1)$$

Logistic regression models the probability of a response variable been 0 or 1 with respect to some data set. We assume a linear relationship between the response variable and log-odds also known as the logit of the event $Y_i = 1$. Statistically, this relationship can be written as

$$l = log_e\left(\frac{\alpha_i}{1-\alpha_i}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \quad (3.2)$$

Where
l = log-odds
e = the base of the logarithm and
β_i = model parameters.
By replacing α_i with p equation (3.2) becomes

$$log_e\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

$$\frac{p}{1-p} = e^{\beta_0+\beta_1 X_1+\beta_2 X_2} \quad (3.3)$$

By making p the subject of the formula in (3.3) we obtain

$$p = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2}}{1+ e^{\beta_0+\beta_1 X_1+\beta_2 X_2}} \quad (3.4)$$

Dividing both numerator and denominator of (3.4) by $e^{\beta_0+\beta_1 X_1+\beta_2 X_2}$ we get

$$p = \frac{1}{1+ e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2)}} \quad (3.5)$$

Equation 3.5 is a simple logistic equation

Predicting the category of dependent variable for a given vector X of independent variables. Through logistic regression we have

$$p = \frac{1}{1+ e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2)}}$$

Thus we choose a cut-off of probability say 'p' and if $P(Yi = 1)$ then we can say that Yi belongs to class 1 otherwise 0.

3.6.1 Statistical Properties of the Logistic Growth Model

A simple logistic growth model with the following mode specification is considered:

$$y = \frac{\beta_0}{1+ e^{(\beta_1+\beta_2 X)}} \quad (3.6)$$

Where,

β_0= growth rate

β_1 = The upper asymptotes where the independent variable tends to infinity

β_2 = growth range

X= is a set of independent variable , $i = 1,2, \dots, 9$

The growth rate is obtained by taking the derivative of (3.6) with respect to x

$$\frac{\partial y}{\partial x} = \frac{-\beta_0}{\left(1+ e^{\beta_1+\beta_2 X}\right)^2} \quad (3.7)$$

The linear form of (3.6) is derived as follow

$$y^{-1} = \frac{1+ e^{(\beta_1+\beta_2 X)}}{\beta_0}$$

$$\frac{\beta_0}{y} = 1 + e^{\beta_1+\beta_2 X} \quad (3.8)$$

$$ln\left(\frac{\beta_0}{y} - 1\right) = \beta_1 + \beta_2 X \quad (3.9)$$

3.6.2 Asymptotes of the Logistic Growth Regression

Firstly, the parameters β_1 and β_2 are taken to be zero

$$\beta_1 = 0 \Rightarrow y = \frac{\beta_0}{1+ e^{(\beta_2 X)}} \quad (3.10)$$

$$\beta_2 = 0 \Rightarrow y = \frac{\beta_0}{1+ e^{\beta_1}} \quad (3.11)$$

3.6.3 Point of Inflection of the Logistic Regression Model

From (3.8) we get

$$y = \beta_0\left(1+ e^{(\beta_1+\beta_2 X)}\right)^{-1}$$

$$y' = \frac{-\beta_0\beta_2\, e^{(\beta_1+\beta_2 X)}}{(1+e^{(\beta_1+\beta_2 X)})^2} \qquad (3.12)$$

$$y'' = \frac{-\beta_0\beta_2{}^2\, e^{(\beta_1+\beta_2 X)}\left(1+ e^{(\beta_1+\beta_2 X)}\right)^2 + 2\beta_0\beta_2{}^2\, e^{2(\beta_1+\beta_2 X)(1+e^{(\beta_1+\beta_2 X)})}}{(1+ e^{(\beta_1+\beta_2 X)})^4}$$

$$= \frac{-\beta_0\beta_2{}^2\, e^{(\beta_1+\beta_2 X)}\left(1+ e^{(\beta_1+\beta_2 X)}\right) + 2\beta_0\beta_2{}^2\, e^{2(\beta_1+\beta_2 X)}}{(1+ e^{(\beta_1+\beta_2 X)})^3} = 0$$

$$\Rightarrow -\beta_0\beta_2{}^2\, e^{(\beta_1+\beta_2 X)}\left(1+ e^{(\beta_1+\beta_2 X)}\right) + 2\beta_0\beta_2{}^2\, e^{2(\beta_1+\beta_2 X)} = 0$$

$$\Rightarrow -\beta_0\beta_2{}^2\left(1+ e^{(\beta_1+\beta_2 X)}\right) + 2\beta_0\beta_2{}^2\, e^{(\beta_1+\beta_2 X)} = 0$$

$$\left(1+ e^{(\beta_1+\beta_2 X)}\right) = 2e^{(\beta_1+\beta_2 X)}$$

$$e^{(\ \ _1+\beta_2 X)} = 1$$

By taking the log of both sides we have

$$x = \frac{-\beta_1}{\beta_2} \qquad (3.13)$$

3.6.4 Model Specification

Logit regression model will be used to obtain the willingness to pay of the households for an improved electricity supply and the factors influencing the household level of compliance

The Logit regression model is as specified below

$$P_i = E\left(Y = {}^{1}\!/_{X_i}\right) = \frac{1}{1+e^{-(\beta_\circ+\beta i X i)}} \qquad (3.14)$$

Where Pi is a probability that Yi = 1 (WTP for improved electricity supply services)

X_i =is a set of independent variable , $i = 1,2,\dots,9$

Y is dependent variable (Responses of household to willingness to pay question which is either 1 if Yes or 0 if No)

$ß_0$ is the intercept which is constant

$ß_1$ is the coefficient of the price that the households are willing to pay for improved electricity supply.

The coefficients estimates obtained were used to calculate the mean willingness to pay of the households. The Mean willingness to pay for improved electricity supply by households is:

$$Mean\ WTP = \frac{1}{|\beta_1|} * ln(1+\exp\beta_\circ) \qquad (3.15)$$

$ß_0$ and $ß_1$ are absolute coefficient estimates from the logistic regression and the Mean WTP is the mean for the improved electricity supply by households.

Similarly, the Logit regression model is as specified below

$$P_i = E\left(Y = {}^{1}\!/_{X_i}\right) = \frac{1}{1+e^{-(\beta_\circ+\beta i X i)}} \qquad (3.16)$$

Where Pi is a probability that Yi = 1 (WTP for improved electricity supply services)

Xi is a set of independent variables

Y is dependent variable (Responses of household to willingness to pay question which is either 1 if Yes or 0 if No)

$ß_0$ is the intercept which is constant *ß₁* is the coefficient of the price that the households are willing to pay for improved electricity supply. For the purpose of this study, the set of independent variables *Xi* are the demographic factors (DEMGP) and the socioeconomic factors (SEF).Hence;

$$P_i = E(Y = 1/X_i) = \frac{1}{1 + e^{-(\beta_0 + \beta_i DEMGP_1 + \beta_3 SEF_i)}} \tag{3.17}$$

where i is (i)th household.

Let us denote:

$$Z_i = \beta_0 + \beta' X_i, \tag{3.18}$$

which is modified for the purpose of this study to form:

$$Z_i = \beta_0 + \beta_1 DEMGP_i + \beta_2 SEF_i \tag{3.19}$$

and following formula:

$$P_i = \frac{1}{1 + e^{-z_i}} = \frac{e^{zi}}{1 + e^{z_i}} = F(Z_i), \tag{3.20}$$

is distribution function of the logistic distribution.
By the logarithm we obtain LOGIT:

$$\text{In}\left(\frac{P_i}{1 - P_i}\right) = Z_i = \beta_0 + \beta' X_i, \tag{3.21}$$

which is for the purpose of this study modified to form:

$$\text{In}\left(\frac{P_i}{1 - P_i}\right) = Z_i = \beta_0 + \beta_1 DEMGP_i + \beta_2 SEF_i \tag{3.22 }$$

To estimate the unknown parameters of the LOGIT model we cannot use classical method of least squares, but with quality software we can use the maximum likelihood method.

From the common formula of the log-likelihood function,

$$\text{In } L(\beta_{0,}\beta) = \sum_{i-1}^{N}\left[Y_i \, In\left(\frac{e^{zi}}{1 + e^{zi}}\right) + (1 - Y_i) In\left(1 - \frac{e^{zi}}{1 + e^{zi}}\right)\right], \tag{3.23}$$

and for the purpose of this study is:

$$\text{In } L(\beta_0, \beta_1, \beta_3) \tag{3.24}$$

3.6.5 Model of Fit Statistic

According to Pallant, (2011), the Hosmer-Lemeshow goodness-of –fit statistic was used to determine if the model sufficiently explains the data. The model is fit when the P-value is greater than 0.05 and vice-versa. Also, the Likelihood Ratio (LR) statistic was used to test the relationships between the consumers' willingness to pay for electricity supply in Port Harcourt City Local Government Area of Rivers state and its associated challenging factors that influences consumers not to pay at P<0.05. That is to test the extent to which the proximate factors influence the consumer's willingness to pay for electricity supply in Port Harcourt City Local Government Area Rivers state.

3.7 Probit Model

In statistics, a probit model is a type of regression where the dependent variable can only take two values, for example married or not married. The name is from probability + unit. We also have a vector of regressors X, which are assumed to influence the outcome Y. Specifically, we assume that the model takes form

$$\Pr(Y = 1/X) = \phi(X^i/\beta) \tag{3.25}$$

Where Pr denotes probability, and Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The parameters β are typically estimated using the maximum likelihood. It is also possible to motivate the Probit model as a latent variable model. Suppose there exists an auxiliary random variable

$$Y^* = X^*\beta + \varepsilon \tag{3.26}$$

where ε ~ N(0, 1). Then Y can be viewed as an indicator for whether this latent variable is positive:

$$Y = 1(X > 0) = \begin{cases} 1 \quad if \quad Y^* > 0 \quad -\varepsilon > X^*\beta \\ \\ O \quad Otherwise \end{cases} \tag{3.27}$$

The use of the standard normal distribution causes no loss of generality compared with using an arbitrary mean and standard deviation because adding a fixed amount to the mean can be compensated by subtracting the same amount from the intercept, and multiplying the standard deviation by a fixed amount can be compensated by multiplying the weights by the same amount.

To see that the two models are equivalent, note that;

$$\Pr(Y = 1/X) = \Pr ob(Y^* >)) = \Pr ob(X^i\beta + \varepsilon > 0) \tag{3.28}$$

$$= \Pr ob(\varepsilon > -X^i\beta)$$

$$= \Pr ob(\varepsilon < X^i\beta) \text{ (By the symmetry of the normal distribution)}$$

$$= \phi(X^i/\beta)$$

3.7.1 Method of Estimating Probit Model

To estimate the unknown parameters of the probit model we cannot use classical methods of least squares either, but we can use a universal maximum likelihood method. From the common formula of the log-likelihood function, specified Christensen (1990).

$$\text{In } L(\beta_{0,}\beta) = \sum_{i-1}^{N} \left[Y_i \; In\left(FZ_i\right) + (1-Y_i) In\left(1 - F(Z_i)\right)\right],$$

after substitution:

$$L(\beta_{0,}\beta) = \sum_{i-1}^{N} \left[Y_i \; In\left(F(\beta_0 + \beta' X_i)\right) + (1-Y_i) In\left(1 - F(\beta_0 + \beta' X_i)\right)\right], \tag{3.29}$$

for the purpose of this study:

In $L(\beta_1, \beta_2,)$

$$= \sum_{i-1}^{N} \Big[\; CWP\_5_I \;\; In(F(\beta_0 + \beta_1 DEMGP_i + \beta_2 SEF_i))$$

$$+ (1 + CWP\_5_i) \;\; In\big(1 - F(e\beta_0 + \beta_1 DEMGP_i + \beta_2 SEF_{ii}\big))\Big] \qquad (3.30)$$

Where CWP is the consumers' willingness to pay and distribution function:

$$F(\beta_0 + \beta' X_i) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{(\beta_0 + \beta' X_i)} \frac{-z^2}{e^2 dz,}$$

after distribution for the purpose of this study is:

$$F(\beta_0 + \beta_1 DEMGP_i + \beta_2 SEF_i) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{(\beta_0 + \beta_1 DEMGP_i + \beta_2 SEF_i)} \frac{-z^2}{e^2 dz,} \qquad (3.31)$$

Where;

CWP is Consumers' willingness to pay

DEMGP are the demographic factors influencing CWP

SEF are the socioeconomic factors influencing CWP

3.8 The Tobit Model

Tobit model are said to have latent variable models that don't involve binary dependent variables Say y* = xβ + u, u|x ~ Normal (0,σ2) (3.32)
But we only observe y = max (0, y*), The Tobit model uses MLE to estimate both β and σ for this model and it is Important to realize that β estimates the effect of x on y*, the latent variable, not y.

RESULTS

This chapter is based on the presentation of results of the test carried out in this research work and the results are presented as thus:

4.1 Correlation Analysis

This was done to determine the level of association between Consumer's Willingness to Pay with due consideration to the Demographic and Socio Economic factors and the results is shown in Table 4.2 below.

Table 4.1: Results of the Correlation Analysis for Consumer's Willingness to Pay, Demographic and Socio-economic factors

Variables	cwp	demo	sef
cwp	1.0000		
demo	0.1828	1.0000	
sef	0.1001	0.1755	1.0000

Note: CWP represents consumer's willingness to pay
Demo represents demographic factors
Sef represents consumer's Socioeconomic factors

4.2 Probit Regression Model

Probit model is based on benefit theory and rational choice approach. According to the rational choice approach, individuals choose the ones that will benefit the most from the options they face. The dependent variable was defined as "1" for consumer's willingness to pay and "0" for non- consumer's willingness to pay as in the logit model. The variables for the study is binary, and we will use a probit model. Thus, our model will calculate a predicted probability of Demographic and Socioeconomic factors based on our predictors (Consumers' Willingness to Pay). The probit model does so using the cumulative distribution function of the standard normal. Also, the model goodness of fit test was also estimated to determine the robustness of the model. The results of the probit regression model in table 4.2 below

Table 4.2: Results of the Probit Regression Model

```
Iteration 0:   log likelihood -  495.78619
Iteration 1:   log likelihood -  473.40446
Iteration 2:   log likelihood -  473.20194
Iteration 3:   log likelihood -  473.20193

Probit regression                          Number of obs     -      1,338
                                           LR chi2(2)        -      45.17
                                           Prob > chi2       -     0.0000
Log likelihood -  473.20193                Pseudo R2         -     0.0456
```

CONWP	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
DEMGP	.5676279	.0962828	5.90	0.000	.3789172	.7563386
sef	.3529775	.1517472	2.33	0.020	.0555586	.6503965
_cons	-1.377612	.0570526	-24.15	0.000	-1.489433	-1.265791

The goodness of fit test for probit regression results are shown below in table 4.3

Table 4.3: Goodness of Fit Test Results for the Probit Regression Model

Measures of Fit for probit of CONWP

Log-Lik Intercept Only:	-495.786	Log-Lik Full Model:	-473.202
D(1335):	946.404	LR(2):	45.169
		Prob > LR:	0.000
McFadden's R2:	0.046	McFadden's Adj R2:	0.040
Maximum Likelihood R2:	0.033	Cragg & Uhler's R2:	0.063
McKelvey and Zavoina's R2:	0.071	Efron's R2:	0.037
Variance of y*:	1.076	Variance of error:	1.000
Count R2:	0.878	Adj Count R2:	0.000
AIC:	0.712	AIC*n:	952.404
BIC:	-8664.169	BIC':	-30.771

4.3 Tobit Regression Model

The tobit model, also called a censored regression model, is designed to estimate linear relationships between variables when there is either left- or right-censoring in the dependent variable (also known as censoring from below and above, respectively). Censoring from above takes place when cases with a value at or above some threshold, all take on the value of that threshold, so that the true value might be equal to the threshold, but it might also be higher. In the case of censoring from below, values those that fall at or below some threshold are censored. Also, the model goodness of fit test was also estimated to determine the robustness of the model. The results for the tobit regression model estimation is shown in table 4.4 below

Table 4.4: Results for the Tobit Regression Model

Tobit regression		Number of obs =	1,338
		Uncensored =	163
Limits: lower = 0		Left-censored =	1,175
upper = +inf		Right-censored =	0
		LR chi2(2) =	44.72
		Prob > chi2 =	0.0000
Log likelihood = -617.10793		Pseudo R2 =	0.0350

CONWP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
DEMGP	.8946461	.1609136	5.56	0.000	.5789752	1.210317
sef	.5464565	.239574	2.28	0.023	.0764743	1.016439
_cons	-2.207681	.1948369	-11.33	0.000	-2.5899	-1.825461
var(e.CONWP)	2.718927	.3811789			2.065168	3.579642

The results for the estimation of the goodness of fit test for the tobit regression model is shown in table 4.5

Table 4.5: Goodness of Fit Test for the Dummy Variable of Tobit Regression Model

Log-Lik Intercept Only:	-907.564	Log-Lik Full Model:	-898.599
D(1333):	1797.197	LR(2):	17.931
		Prob > LR:	0.000
McFadden's R2:	0.010	McFadden's Adj R2:	0.004
Maximum Likelihood R2:	0.013	Cragg & Uhler's R2:	0.018
McKelvey and Zavoina's R2:	0.021	Efron's R2:	0.014
Variance of y*:	1.021	Variance of error:	1.000
Count R2:	0.590	Adj Count R2:	0.011
AIC:	1.351	AIC*n:	1807.197
BIC:	-7798.978	BIC':	-3.533

4.4 Logistic Regression Model

This was used to established a relationship between the consumer's willingness to pay and one or more the demographic and socioeconomic factors by estimating probabilities. Also, the model goodness of fit test was also estimated to determine the robustness of the model. The results for the logistic regression model are shown in table 4.6 below;

Table 4.6: Results for the Logistic Regression Model

Logistic regression	Number of obs	=	1,338
	LR chi2(2)	=	44.83
	Prob > chi2	=	0.0000
Log likelihood = -473.37201	Pseudo R2	=	0.0452

cwp	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
demo	2.84071	.4992771	5.94	0.000	2.012897	4.008965
sef	1.840949	.4885493	2.30	0.021	1.094336	3.096941
_cons	.092529	.0104836	-21.01	0.000	.074103	.1155366

Note: _cons estimates baseline odds.

The results for the goodness of fit test for logistic regression model is shown in table 4.7 below.

Table 4.7: Goodness of Fit test for Logistic Regression Model

Measures of Fit for logistic of cwp			
Log-Lik Intercept Only:	-495.786	Log-Lik Full Model:	-473.372
D(1335):	946.744	LR(2):	44.828
		Prob > LR:	0.000
McFadden's R2:	0.045	McFadden's Adj R2:	0.039
Maximum Likelihood R2:	0.033	Cragg & Uhler's R2:	0.063
McKelvey and Zavoina's R2:	0.071	Efron's R2:	0.037
Variance of y*:	3.543	Variance of error:	3.290
Count R2:	0.878	Adj Count R2:	0.000
AIC:	0.712	AIC*n:	952.744
BIC:	-8663.829	BIC':	-30.430

4.5 Summary of the Goodness of Fit Test Probit, Tobit and Logistic Regression Model

The summary of the goodness of fit test probit, tobit and logistic regression model was done to check the robustness of each of the model. The summary of the results based on the goodness of fit test for probit, tobit and logistic regression model is shown in table 4.8

Table 4.8: Summary of the Goodness of Fit Test for probit, tobit and Logistic Regression Model

Measures of Fit for Consumer's Willingness to Pay			
Log-like full model	Probit	Tobit	Logistic
LR(2)	-473.202	-898.599	-473.372
Mac Fadden's AdjR^2	45.169	17.931	44.828
Gragg&Uhlers R^2	0.040	0.018	0.063
Efron's R^2	0.037	0.014	0.037
Variance of Error	1.000	1.000	3.290
Adj Count R^2	0.000	0.011	0.000
Pseudo R^2	0.0456	0.0350	0.0452
Prob>chi^2	0.000	0.000	0.000
AIC	952.404	1807.197	952.744
BIC	-30.771	-3.533	-30.430

DISCUSSION

5.1 Correlation Analysis

This was done to determine the level of association between Consumers' Willingness to Pay with due consideration to the Demographic and Socioeconomic factors and the results is shown in Table 4.1 . Table 4.1 contains the results of the correlation analysis for consumer's willingness to pay, demographic and socio-economic factors and the results revealed that there is positive association between consumers' willingness to pay and the demographic factors associated with consumers' status in the society with a correlation coefficient of (0.1828). Also, that there is positive association between consumers' willingness to pay and the socio-economic status of consumers in the society with a correlation coefficient of (0.1001). It found also that there is positive association between demographic factors and the socioeconomic status of consumer's in the society with a correlation coefficient of (0.1755).

5.2 Probit Regression Model

Table 4.2 contains the Results of the estimated Probit Regression Model. The Correlation between consumers' willingness to pay and other variables according to probit model was found to be as follows;

Consumers' Willingness to pay(CNWP) = -1.377612 + 0.5676279 DEMGP + 0.3529775 SEF

From the above expression, a coefficient of demographic factors (DEMGP) of 0.5676279 indicates that an increase in demographic factors increases the predicted probability of consumers' willingness to pay (CNWP) for electricity bills. Similarly, a coefficient of socioeconomic factors (SEF) of 0.3529775 means that an increase in socioeconomic factors will increases the predicted probability of consumer's willingness to pay for electricity bills. When the results of binary probit model are examined in Table 4.2, it is seen that as in logit model, all the variables are significant ($p<0.05$). The constant term is -1.377612. This means that if all of the predictors (socioeconomic factors and demographic factors) are evaluated at zero, the predicted probability of consumer's willingness to pay is F(-2.797884) = 0.002571929.

The obtained LR statistic was found to be significant according to $\chi 2$ value with 45.17 degrees of freedom in the probit model, the demography and socioeconomic variables were found to be statistically. Marginal effects were calculated following the probit model estimate. To interpret the coefficients of the probit model as in the Logit model; The mean of the independent variables was evaluated and marginal effects were used. The results obtained here was synonymous to Daniel (2014) investigation on the willingness to pay for Improved Electricity Supply in Ghana using probit model. In Daniel (2014), it found that the results from our analysis indicated that, households in Ghana are prepared to pay on the average about ¢0.2734 for a kilowatt- hour which is about one and a half times more than what they are paying currently. An econometric analysis of the factors that influence households' WTP for improved electricity supply indicates that household income, sex, household size, secondary and tertiary level education are the significant factors.

5.3 Tobit Model

The results for Tobit model estimation is shown in Table 4.4. The table shows that the lower limit of the consumers' willingness to pay was zero and left censored. Accordingly,1.175 observations were censored from the left and 163 observations were not censored. When the results for Tobit model are examined, it is seen that all variables are significant. The parameter given as sigma is the estimated standard error of the regression. The obtained 2.718927 value in the regression model. Correlation between consumers' willingness to pay (CNWP) and other variables according to Tobit model was found to be as follows;

$$Consumer's \quad willingness \quad to \quad pay(CNWP) = -2.207681 + 0.8946461 DEMGP + 0.5464565 SEF$$

The coefficient of demographic factors (DEMGP) is 0.8946461 and it is positively and statistically significant from zero. This means that an increase in demographic factors will lead to an expected to corresponding increase in consumers' willingness to pay (CNWP) by 0.8946461 points while holding all other variables in the model constant. Thus, the higher the demographic factors (DEMGP), the higher the predicted consumers' willingness to pay (CNWP). The coefficient of socioeconomic factors (SEF) is 0.5464565 and it is positively and statistically significant from zero. This means that an increase in socioeconomic factors will lead to an expected to corresponding increase in consumers' willingness to pay by 0.5464565 points while holding all other variables in the model constant. Thus, the higher the demographic factors, the higher the predicted consumer's willingness to pay.

The **t** test statistic for the intercept, **_**cons, is $(-2.207681/0.1948369) = -11.330918$ with an associated p-value of < 0.001. If we set our alpha level at 0.05, we would reject the null hypothesis and conclude that **_**cons have been found to be statistically different from zero given socioeconomic and demographic factors are in the model and evaluated at zero. The results of this study was synonymous to in Öznur *et al* (2020), evaluate residential consumers' willingness to pay to avoid power outages in South Korea using tobit model and Ju-Hee *et al* (2019), studied on dependent dummy variable models: an application of logit, probit and tobit models on survey data. For Öznur *et al* (2020), the different regression models may be preferred. Logit, probit and Tobit model coefficient estimates and marginal effects were calculated. In addition, Akaike Information Criterion(AIC) and Bayesian Information Criterion (BIC) values were obtained from the model selection criteria for these 3 models. The results show that the coefficients of the model parameters were statistically different from zero. For Ju-Hee., *et al* (2019), evaluate residential consumers' willingness to pay to avoid power outages in South Korea using tobit model, it was found that the respondents understood the CV question well and gave meaningful answers. The results show that the mean of households' monthly WTP amounts to KRW 1522 (USD 1.41) and all the parameters of the models were statistically significant. Converting it into an annual value and then expanding the value to the country indicate that the annual national value amounts to KRW 360.7 billion (USD 335.3 million). Since a substantial amount of investments should be made by power suppliers to prevent power outages in the residential sector, this value may be accepted as the upper limit of the benefits ensuing from those investments.

5.4 Binary Logistic Model

The results for Tobit model estimation is shown in Table 4.6. Based on the information onn table 4.6, Correlation between consumers' willingness to pay (CNWP) and other variables according to binary logistic model was found to be as follows;

$$Consumer's\ \ willingness\ \ to\ \ pay(CNWP) = 0.092529 + 2.84071DEMGP + 1.840949SEF$$

The coefficient for demographic factors (DEMGP) is 2.84071. This indicates that an increase of 2.84071 is expected in the log odds of consumers' willingness to pay with a one-unit increase in demographic factors (in other words, for consumers' willingness to pay compared to those who are not). This coefficient is also statistically significant, with a Wald test value (z) of 5,94. This is because the Wald test is statistically significant, the confidence interval for the coefficient does not include 0. Similarly, the coefficient for socioeconomic factors(SEF) is 1.840949. This indicates that an increase of 1.840949 is expected in the log odds of consumers' willingness to pay with a one-unit increase in socioeconomic factors (in other words, for consumers' willingness to pay compared to those who are not). This coefficient is also statistically significant, with a Wald test value (z) of 2.30. Because the Wald test is statistically significant, the confidence interval for the coefficient does not include 0.

5.5 The Best Fitted Model in Modeling Consumer Willingness to Pay for Electricity Bill in Port Harcourt City Local Government Area of Rivers State

Table 4.8 contains the summary of the goodness of fit test for probit, tobit and logistic regression model. The models were compared on the basis of their information criteria and it was found that probit model have AIC and BIC values of 952.404 and -30.771, Tobit model have 1807.197 and -3.533 and logit model have 952.744 and -30.430 respectively. Therefore, it can be said that probit model is better than tobit and logit models.

5.6 The Coefficient of the Model Associated with Demographic and Socio-economic Factors that Influenced Consumer Willingness to Pay for Electricity Bill in Port Harcourt City Local Government Area of Rivers State

The results obtained show that Probit model is better than Tobit and logit models. Therefore, to determine the coefficient of the model associated with demographic and socio-economic factors that influenced consumer willingness to pay for electricity bill in Port Harcourt City Local Government Area of Rivers State will be done using Probit model. Hence, the coefficient of the demographic and socioeconomic factors is 0.5676279 and 0.3529775. This simply means that an increase in demographic and socioeconomic factors increases the percentage of consumers' willingness to pay for electricity bills by 56.763 and 35.28 percentage respectively.

6.1 Conclusion

Based on the findings of the study, we can conclude that consumers are willing to pay for electricity Bill in Port Harcourt City Local Government Area of Rivers State. However, there are some of the factors that are correlated with consumers' willingness to pay for electricity bill such factors are demographic (age, educational status, occupation, household size) and socioeconomic (income, monthly expenditure, marital status) factors. Also, the probability associated with demographic and socioeconomic increases the predicted probability of consumers' willingness to pay for electricity bills. When the models were compared, the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were found that probit model has a better than tobit and logit models in estimating regression models used with censored data. In the study, the variables found to be significant in logit and probit models were found to be significant in Tobit model. The Tobit model uses all data, including censored information, and allows for the estimation of consistent parameters.

6.2 Recommendations

The following recommendations were made based on the results obtained in the study:

i. There is need for diversity of sources of power supply in the study area, local communities should take advantage of a variety of plants that are more accessible.

ii. There is need for government support for the consumers of electricity supply in the form of payment of electricity bills.
iii. Government should endeavor to install pre-paid meter for all electricity consumers and eradicate the use of analogy meters or estimated electricity billing.
iv. There should be awareness campaign on the need for electricity users to pay electricity bill in other to avoid disconnection.
v. The electricity end users should avoid illegal connection as this has dual negative effects of short changing the PHCN and possible damage to PHCN equipment.

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