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Addressing the Problem of Simultaneity in Cargo Shippers' Port Utility Models: An Econometric Analysis

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Abstract

The traditional method of modelling shippers' port utility behaviour has been the Random Utility models. The robustness of such models and their variants in producing unbiased estimates cannot be guaranteed in the presence of simultaneity. In this paper, we demonstrate how interrelationship among variables that describe shippers' port utilization model can lead to simultaneity problem. Using port level shipment data from the Nigeria Ports Authority, we then show how this problem can be eliminated using Two-Stage Least Squares technique. Our post estimation test results confirm the robustness of this technique.

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1 Introduction

Port utility refers to the satisfaction a shipper derives from choosing a particular port and using it for shipment making purposes. This satisfaction is a perceived one and can be measured in utils. But in considering the actual choice (i.e. port) and the shipments made, we can extend this theory to include his level of utilization of a particular port. Shipper's level of port utilization can then be taken as a measure of the total quantity of shipments which he sends or receives from a particular port based on expected utility. This is same as volume of cargo handled in his port of choice. Onwuegbuchunam [1] and Tongzon [2] posit that a shipper's utilization of any port is a function of his perception about attributes related to shipments and ports. These attributes are: the distance of that port to his warehouse or market for his product, crane efficiency and turn-round time at the port. Turn-round time in any port however, is a function of crane efficiency, the volume of cargo discharged or loaded (or both), number of ships berthed at the port, level of cargo handling facilities at the port and berth occupancy. Mathematically, these variables are related in a system of equations. Implicitly, what appears as a regressor in one equation may be also a regressand in another. This feature gives rise to simultaneous equation bias or simultaneity problem in models describing shipper port utilization behaviour.

In practice, the interrelationship among these variables (attributes) can be better captured and modelled by employing instrumental variable regression technique. The selection and application of suitable instruments eliminate the problem of correlated error terms. In this paper we adopt instrumental variable regression methodology for assessment of port level shippers utility model to account for the problem of simultaneity.

2 Objectives of Study

The objectives of this paper are to:

(i) Assess the structural characteristics of cargo shippers' port utility model

(ii) Conduct identification of the formulated model.

(iii) Estimate the structural parameters of the model using Two-Stage Least Squares.

(iv) Conduct model validation tests (R^2, RMSE and F-test) on the estimated model in (iii) above.

3 Literature Review

The traditional method for estimating port utility behaviour of port users particularly the shippers has been the quantile choice models especially the Random Utility Models (RUM). The appeal in the widespread use of random utility models stems from its basis on the theory of consumer behaviour. This theory posits that given a set of ports with equally likely attributes; shippers would choose port(s) which maximize their utility or rather reduce their generalized cost of transport (see McFadden, [3]).

The random utility framework has been applied by many researchers in modelling shipper port choice characteristics. Notable among these are: Gonzalez [4], Malchow [5], Tuna [6], Veldman [7], Lirn [8], Malchow and Kanafani [9]. Others include: Tongzon [2], [10], Song et al. [11], Guy and Urli [12], De Langen [13], Magala and Sammons [14], Panayides and Song [15] and Onwuegbuchunam [1]. The basic assumption of RUM is that the expected utility which a shipper derives from choosing a particular port for shipment making is dependent on attributes of the shipper, the consignment (shipment) and the port. That is, we generally estimate the probability that a shipper will utilize a particular port given his expectation of the utility regarding the aforementioned attributes. In this case, the parameters of the utility model are regarded as fixed. However, recent studies have shown that these parameters vary and the random nature of these parameters has given way to choice modelling based on random coefficient approach. Both random utility and random coefficient modelling frameworks may not efficient in the presence of serial correlation. Again, modelling port utilization behaviour of shippers usually involves a system of equations describing variables which are endogenous in one equation and also appear as exogenous in the other. Thus, we are faced with simultaneity problem which cannot be resolved under Random Utility and Random Coefficient modelling framework as these basically involve single equation models.

In contrast to single-equation models, in simultaneous-equation models, more than one dependent or endogenous variable is involved; necessitating as many equations as the number of endogenous variables. A unique feature of simultaneous-equation models is that the endogenous variable in one equation may appear as an explanatory variable in another equation of the system. As a consequence, such an endogenous explanatory variable becomes stochastic and is usually correlated with the disturbance term of the equation in which it appears as an explanatory variable. In this situation, the classical OLS method may not be applied because the estimators thus obtained are not consistent; i.e., they do not converge to their true population values no matter how large the sample size. In these circumstances, alternative estimating techniques have been developed; such as the Indirect Least Squares (ILS) technique, the Two-Stage Least Squares (2SLS) technique; among others (Gujurati, [16]). In the subsequent section, we describe the generic simultaneous equation systems and demonstrate how their estimability can be determined through 'Identification'

Solving Simultaneous Equations: Derivation of the Reduced Form of the Model:

The structural form of simultaneous equation model is:

$$\beta_{11}Y_{t1} + \beta_{21}Y_{t2} + \dots + \beta_{m1}Y_{tm} + \gamma_{11}X_{t1} + \dots + \gamma_{k1}X_{tk} + \varepsilon_{t_1}$$
$$\beta_{12}Y_{t1} + \beta_{22}Y_{t2} + \dots + \beta_{2}Y_{tm} + \gamma_{12}X_{t1} + \dots + \gamma_{2}X_{tk} + \varepsilon_{t_2}$$
$$\vdots$$
$$\beta_{1m}Y_{t1} + \beta_{2m}Y_{t2} + \dots + \beta_{mm}Y_{tm} + \gamma_{1m}X_{t1} + \dots + \gamma_{km}X_{tk} + \varepsilon_{tm}$$

There are 'M' equations and 'M' endogenous variables denoted Y_1, Y_2, …, Y_m. There are 'K' exogenous variables, X_1, X_2, …,X_k that may include predetermined values of Y_1, Y_2, …, Y_m as well. The first element of X_t will usually be constant 1. Finally, ε_{t1}, ε_{t2},…, ε_{tm} are the structural disturbances. The subscript 't' will be used to index observations, t = 1, 2, …, T.

In matrix terms, the system may be written:

$$\begin{bmatrix} Y_1 & Y_2 & \cdots & Y_m \end{bmatrix}_{\mathrm{t}} \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1m} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ \beta_{m1} & \beta_{m2} & \cdots & \beta_{mm} \end{bmatrix} +$$

$$\begin{bmatrix} X_1 & X_2 & \cdots & X_k \end{bmatrix}_t \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1m} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ \gamma_{k1} & \gamma_{k2} & \cdots & \gamma_{km} \end{bmatrix} = \begin{bmatrix} \varepsilon_1 & \varepsilon_2 & \cdots & \varepsilon_m \end{bmatrix}_{\mathrm{t}}$$

or

$$Y_t^T \mathbf{\Gamma} + X_t^T \boldsymbol{\beta} = \mathbf{E}_t^T$$

Each column of the parameter matrices is the vector of coefficients in a particular equation, whereas each row applies to a specific variable. The solution of the system of equations determining 'Y_t^T' in terms of 'X_t^T' and 'E_t^T' is the reduced form of the model:

$$Y_t^T = \left[X_1 \quad X_2 \quad \cdots \quad X_k\right]_t \begin{bmatrix} \Pi_{11} & \Pi_{12} & \cdots & \Pi_{1m} \\ \Pi_{21} & \Pi_{22} & \cdots & \Pi_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ \Pi_{k1} & \Pi_{k2} & \cdots & \Pi_{km} \end{bmatrix} + \left[V_1 \quad V_2 \quad \cdots \quad V_m\right]_{\mathrm{t}}$$

$$= -X_t^T \boldsymbol{\beta}\boldsymbol{\Gamma}^{-1} + \mathbf{E}_t^T \boldsymbol{\Gamma}^{-1}$$
$$= X_t^T \boldsymbol{\Pi} + V_t^T$$

where

$$\boldsymbol{\Pi} = -\boldsymbol{\beta}\boldsymbol{\Gamma}^{-1}.$$

For this solution to exist, $\boldsymbol{\Gamma}$ must be nonsingular (Greene, [17]).

4 Methodology

Data for this study consists of shipments records from the Traffic Department of Nigeria Ports Authority. It consists of port utilization measured as volumes of cargo (in tonnes) shipped/received by shippers at the ports and other port performance measures. The data set covers a period of six years beginning from years 2008 through 2013. Three equations based on our a priori understanding of the relationship and interrelationships existing among the variables were formed. In simultaneous equations with possibly correlated error terms; a dependent variable (endogenous variable) in one equation may turn out to be exogenous variate in the other equation. The equations constitute a simultaneous system of equations describing port utilization by a shipper. Under this circumstance, assumption of independence of error terms in least squares regression modelling is violated hence the application of instrumental variable or Two-Stage Least Squares techniques to address the problem. Shipper's level of port utilization is equivalent to the total shipment (in tonnes) which he sends or receives from a particular port. This is same as Cargo volume handled. But a shipper's utilization of any port has been postulated to be a function of his perception of the distance of that port to his warehouse or market for his product (as he seeks to minimize costs), crane efficiency (speed of cargo handling) and turn-round time at the port. However, turn-round time of any port is a function of cargo volume, number of ships visits at the port (proxy for level of congestion), level of berthing facilities at the port and berth occupancy (a measure of delay). Finally, berth occupancy is dependent on turn round time and draught of the port. The data set consisting of shipments (in tonnes) made in ports, and other port characteristics over a period of time were used for analysis of the structural relationship explained above. The following variables were constructed from the data set:

Cargo volume (Y_{1t}), Shipper's Warehouse Distance from the port (X_{1t});
Turn-round Time at the port (Y_{2t}), Crane Efficiency of the port (X_{2t});
Frequency of Ship Visits at the port (X_{3t}), Berth facilities in the port (X_{4t});
Draught of port channel (X_{5t}) and Berth Occupancy (Y_{3t})

From the foregoing, the complete model for estimation of shipper's port utilization is as given below:

$$Y_{1t} - \beta_{10} - \beta_{22}Y_{2t} - \gamma_{11}X_{1t} - \gamma_{12}X_{2t} = u_{1t} \quad (1)$$

$$Y_{2t} - \beta_{20} - \beta_{21}Y_{1t} - \beta_{23}Y_{3t} - \gamma_{23}X_{3t} - \gamma_{24}X_{4t} = u_{2t} \quad (2)$$

$$Y_{3t} - \beta_{30} - \beta_{32}Y_{2t} - \gamma_{35}X_{5t} = u_{3t} \quad (3)$$

As a precondition for our model estimation, we need to identify the system of equations (1-3) using the rank and order conditions to establish that solution exists. The process of identification is carried out in Tables 1 & 2.

Table 1: Equation Identification Using The Rank Condition

Coefficient of Variables									
EQUATION No.	1	Y1	Y2	Y3	X1	X2	X3	X4	X5
1	$-\beta_{10}$	1	$-\beta_{22}$	0	$-\gamma_{11}$	$-\gamma_{12}$	0	0	0
2	$-\beta_{20}$	$-\beta_{21}$	1	$-\beta_{23}$	0	0	$-\gamma_{23}$	$-\gamma_{24}$	0
3	$-\beta_{30}$	0	$-\beta_{32}$	1	0	0	0	0	$-\gamma_{35}$

RANK CONDITION:

Table 2: Equation Identification Using the Order Condition

	No of Predetermined Variable Excluded	No of Endogenous Variables Included Less Than One	
EQUATION No.	**K - k**	**(m -1)**	**Identified**
1	3	1	Yes
2	3	2	Yes
3	4	1	Yes

From Table 2, the following (m-1) x (m-1) or 2 x 2 matrices are formed with their determinants calculated as shown below:

$$\begin{bmatrix} -\beta_{23} & -\gamma_{23} \\ 1 & 0 \end{bmatrix} = -\gamma_{23} \neq 0, \quad \begin{bmatrix} -\beta_{23} & -\gamma_{24} \\ 1 & 0 \end{bmatrix} \neq 0, \quad \begin{bmatrix} -\beta_{23} & 0 \\ 1 & -\gamma_{35} \end{bmatrix} \neq 0$$

$$\begin{bmatrix} -\gamma_{23} & -\gamma_{24} \\ 0 & 0 \end{bmatrix} = 0, \quad \begin{bmatrix} -\gamma_{23} & 0 \\ 1 & -\gamma_{35} \end{bmatrix} = \gamma_{23}\gamma_{35} \neq 0, \quad \begin{bmatrix} -\gamma_{24} & 0 \\ 1 & -\gamma_{35} \end{bmatrix} \neq 0$$

Therefore the rank of

$$\begin{bmatrix} -\beta_{23} & -\gamma_{23} & -\gamma_{24} & 0 \\ 1 & 0 & 0 & -\gamma_{35} \end{bmatrix}$$

thus formed from Table 1 = 2.

But Rank $(\beta\ \gamma\ \phi) =$ m-1, where m = number of equations; and m-1 = 3-1 = 2, i.e. the rank of $(\beta\ \gamma\ \phi) =$ 2 (as calculated above). From the foregoing, equation 1 is identified since $(\beta\ \gamma\ \phi) =$ m-1 i.e. 2 = 2. Using the same process for identification through rank condition; equation 2 and 3 are also identified. Having established that the system of equations (1-3) is estimable, we now proceed to estimate their structural parameters using the Two-Stage Least Squares technique.

5 Data Presentation and Model Estimation

The descriptive statistics of the sample data are presented in Table 3. The parameters of the structural model were estimated using Two-stage least Squares implemented in Stata for Windows statistical software.

Table 3: Descriptive Statistics of Sample Data

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Cargo Volume (Y_{1t})	74	6,165.257	2,949.496	3,291	15,906
Turn-round Time (Y_{2t})	74	21.297	5.786	12	41
Berth Occupancy (Y_{3t})	74	3.015	0.456	2.19	3.89
Ware House distance (X_{1t})	74	2.993	0.846	1.5	5
Crane Efficiency (X_{2t})	74	13.757	4.277	5	23
Ship Visits (X_{3t})	74	197.297	91.837	79	425
Berth facilities (X_{4t})	74	7.979	0.266	7.47	8.48
Draught (X_{5t})	74	187.932	22.266	142	233

Source: Author

In order to achieve robust results, three major problems must be solved. The first problem is multi-collinearity among these preliminary variables. In a situation of highly correlated variables existing together, the coefficient estimates may change erratically in response to small changes in the model or the data. Table 4 shows the correlation among preliminary variables. As it clearly shows, the correlated coefficient among some variable pairs are higher than 0.8. For examples the variable pair; berth facilities and ship visits are highly correlated with each other (with coefficient above 0.8), while berth facilities and draught of the port also have correlation coefficient above 0.8. Thus when doing regression, it is better to include only one of the two correlated variables so as to avoid multicollinearity.

Table 4: Pairwise Correlation Among All Explanatory Variables

	Berth_Occpncy	**WareHous_dist**	**Crane_Effncy**	**ShipVisits**	**Brth_facil**	**Draught**
Berth_Occpncy	1.000					
WareHous_dist	**-0.378***	1.000				
	[-0.001]					
Crane_Effncy	**-0.509***	**0.662***	1.000			
	[0.000]	[0.000]				
ShipVisits	**-0.829***	**0.475***	**0.609***	1.000		
	[0.000]	[0.000]	[0.000]			
Brth_facil	**-0.753***	**0.481***	**0.655***	**0.866***	1.000	
	[0.000]	[0.000]	[0.000]	[0.000]		
Draught	**-0.696***	**0.516***	**0.727***	**0.835***	**0.948***	1.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	

Correlation coefficient in bold asterisks, p-values in parenthesis.

The second problem is simultaneity problem as previously demonstrated. This problem will be taken care of by applying the two-stage least squares estimation techniques. The third problem originated from the dataset itself. Since in our dataset, the 74 observations represent 74 successive yearly data concerning each variable, these adjacent observations are too similar than those that would be expected under independence. As a result, autocorrelation may occur which can make independent variables more significant than they may really be through smaller standard errors (s.e) for the beta coefficients.

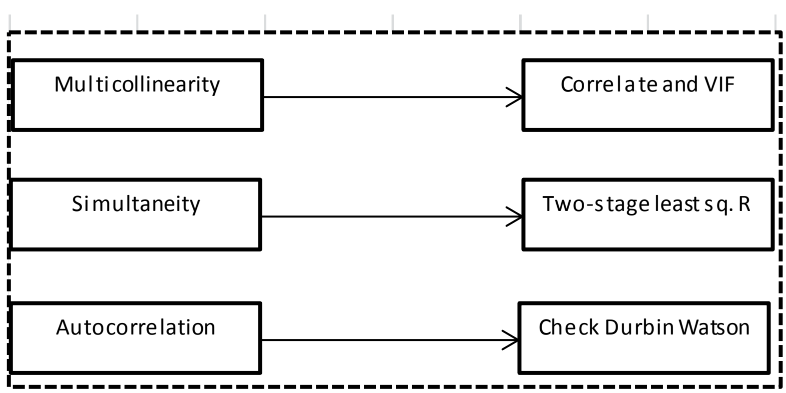

Figure 1: Regression Anomalies and Methods for Correction

These anomalies can be eliminated following the steps outlined in Figure 1. In summary, in the case of shipper port utilization model estimation, multicollinearity, simultaneity, as well as autocorrelation may seriously affect our statistical conclusions.

Steps Followed In Conducting The Two-Stage Least Squares Regression:

1. Regress endogenous variables against all the exogenous variables and save the predicted values of the endogenous variables.
2. Regress original equations, replacing endogenous explanatory variables with their predicted values.

6 Results

In the Table 4, the two-stage least squares regression results are presented. Only the turn-round time variable significantly explains the volume of cargo a shipper handles in a particular port. Therefore the structural coefficient of this variable and the intercept term are significantly different from zero at $\alpha = 0.05$. Although the coefficient of determination (R^2) indicates a poor fit of model to the data (21.1%), this may be due omission of some variable that completely determine cargo volume handled. The F-statistic has a significant p-value (see model fitting information) and indicates that the independent variables jointly explain variations in the Cargo volume (the dependent variable). However, changes in exogenous variable, turnround time are explained by level of berth facilities in the port. The variable berth facility has a structural parameter of value -4.090, which is significant. This model has coefficient of variation of 47% which is higher than that obtained for cargo volume equation. The F-statistic is also significant and implies a better fit of the model. We find also from the regression output that turnround time at the port is the significant variable that

Table 4: 2SLS Regression Output; Structural Parameters of the Port Utility Models

Exogenous Variables	**Estimate**	**Std. Err.**	***t*-stat**	**P>|t|**
		CargoVol[a]		
TurnRoundT: β_{22}	-335.213	93.146	**-3.600**	**0.000**
WareHous_dist: γ_{11}	-698.313	494.917	-1.410	0.160
Crane_Effncy: γ_{12}	44.490	119.585	0.370	0.710
Constant: β_{10}	14782.570	3262.242	4.530	0.000
		TurnRoundT[a]		
CargoVol: β_{21}	0.000	0.001	-0.220	0.823
Berth_Occpncy: β_{23}	-9.694	20.209	-0.480	0.632
ShipVisits: γ_{23}	-0.030	0.063	-0.480	0.632
Brth_facil: γ_{24}	-19.662	4.806	**-4.090**	**0.000**
Constant: β_{20}	215.224	98.929	2.180	0.031
		Berth_Occpncy[a]		
TurnRoundT: β_{32}	0.100	0.043	**2.310**	**0.022**
Draught: γ_{35}	0.006	0.009	0.700	0.488
Constant: β_{30}	-0.335	2.652	-0.130	0.900
		Model Fitting Information		
Equation	**RMSE**	**"R-sq"**	**F-Stat**	**p-value**
CargoVol: Y_{1t}	2675.363	0.211	7.700	0.000
TurnRoundT: Y_{2t}	4.343	0.467	21.850	0.000
Berth_Occpncy: Y_{3t}	0.451	0.050	20.780	0.000
No. of Obs. = 74				

Source: Author. [a]Endogenous Variable

explains variations in Berth Occupancy. The coefficient of variation for this equation is however very low and may be accounted by the few explanatory variable considered.

7 Discussion and Conclusion

We applied the Two-Stage Least Squares (2SLS) method to address the problem associated with correlated error terms in simultaneous equation systems describing port utilization behaviour of shippers. The results obtained and presented in Table 4 agree with our a priori expectation of the relationship between endogenous and exogenous dependent variables. In terms of significance of variables as presented in Table 4, we note that cargo volume achieved in port is inversely related to the turnround time obtainable in that port. That is to say that the lower the numerical value of turnround time, the more shipments will be made there by shippers since they expect to spend little time and hence save cost. Turnround time on the other hand depends on the facilities present in the port. The higher the number of facilities, the less the totality of time (or turnround time) spent by a shipper or ship in a port, hence the negative coefficient of berth facility variable. Finally, we also note in table 4, that berth occupancy is positively related to the turnround time obtainable in a port. This means that high turnround time may be as a result of congestion at the berths and ultimately result in high berth occupancy rate. In terms of Goodness-of-fit of the models, only equation 2 possesses moderate explanatory power with R-squared value of 46.7%. However, equations 1&3 have low explanatory powers given their R-squared values of 21.1% and 5.0% respectively. Although the F-statistic in each model indicates that the coefficients of the explanatory variable are significantly different from zero, the R-Squared and Root Mean Square Error (RMSE) values show that the estimated port utilization model has a poor fit to the data set. One possible explanation for the generally poor fitness of the models is the omission of other relevant variables which affect shipper port utilization model. Thus, future modelling effort should consider models incorporating all the relevant variables in order to improve the fitness of cargo shipper port utility model.

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