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Full Length Research Paper

Consistent estimators of intrinsically linear econometric model of the Nigerian economy

Nwabueze Joy Chioma[1]* and E. Nworuh Godwin[2]

[1]Department of Statistics, Abia State University, Uturu, Abia State, Nigeria.
[2]Department of Project Management, Federal University of Technology Owerri, Imo State, Nigeria.

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This study compares the simulation performance of an operational econometric model of the Nigerian economy. Five estimators namely OLS, $2SPC_4$, $2SPC_6$ and $2SPC_8$ were used to obtain consistent estimators of the structural parameters in an econometric model of the Nigerian economy when some of the equations are non-linear but intrinsically linear. The performance of the estimators was ranked using Friedman's test statistics based on four criteria namely, root mean square error (RMSE), Theils inequality coefficients, bias and variance proportions. The result of this ranking show that $2SPC_6$ and $2SPC_8$ emerged as the best estimators. The least preferred estimators were the OLS and $2SPC_4$ in that order.

Key words: Intrinsically linear model, non-linear, econometric, Friedman test statistic, root mean square error.

INTRODUCTION

Economic modeling has witnessed a lot of developments in recent years. This is because a number of the models are used for the study of multiplier effect and policy analyses for both long and short term forecasting. One common feature of such models is that they consider mainly linear models which contain no lagged endogenous variables. In situations where some of the equations are non-linear in variables or when the predetermined variables are large relative to the sample points, then the regular method of estimating simultaneous equations cannot be used.

Review of analytical and Monte Carlo studies have shown that studies based on two or three equations in the system have not succeeded in answering all the real life questions which are posed in respect of the performance of simultaneous equation estimators especially when the sample data is smaller than the number of stochastic equations or the number of predetermined variables. At the macro level, simultaneous equation models in real-life vary in complexity particularly in the number of structural parameters to be estimated and in the size of the samples. Therefore, building an operational simultaneous equation model is a contribution as well as the search for its most preferred estimator from among potential estimators. This study appraises an operational econometric model of the Nigerian economy built by Olofin and Iyaniwura (1985). The study compares the simulation performance of simultaneous equation methods of estimating individual structural parameters and ordinary least squares (OLS). Nworuh and Nwabueze (2004) reported the principal component estimators of this simultaneous equation model of the Nigerian economy. Their result showed that the six estimators rank differently or vary in their performances. The simulation statistics considered in the work include; bias, root mean square error (RMSE) and Theils inequality coefficients. This study considers the simulation performance of the estimators based on ordinary least squares (OLS), instrumental variables (IV) and principal component techniques (PC) in a model where some of the structural equations are non-linear but intrinsically linear.

*Corresponding author. E-mail: teeubueze@yahoo.co.uk.

EXPERIMENTAL DESIGN

Consider a simultaneous equation model which is intrinsically linear; such a model can be written as:

$$F(y,x) = A\ g\ (z) + u \qquad (1)$$

where z = {y_1, y_2 ….,y_n, x =, x_2…, x_n) denote a vector of p = (n + h) basic variables of which the first n are endogenous variables (denoted by y) and the remaining h are predetermined variables (denoted by x). g(z) is a component column vector of functions of z. A is n × p matrix of the parameters to be estimated and u is a vectors of disturbances.

Identification of each equation in the intrinsically linear system follows almost the same procedures as in the case of the linear system, since all non linear variables are linearized by log transformation. The model in (1) can be written in the most general form as:

$$\beta Y + \Gamma X = U \quad (2)$$

And at period t, the model can be written as:

$$\beta Y_t + \Gamma X_t = U_t \quad (3)$$

Where Y_t includes $Log_\ell\, Y \;\; and \;\; Y$,

X_t includes $Log_e\, X \;\; and \;\; X$

U_t includes $Log_\ell\, U \;\; and \;\; U$

Y_t is the matrix (T × [n-1]) of the remaining included endogenous variables

X_t is (T × h), the matrix of observations on the included predetermined variables

U_t is the t^{th} column of U.

β is the n × n matrix of coefficients of the jointly dependent variables,

Γ is the matrix of coefficient of the predetermined variables.

Thus the reduced form of equation (3) is written as:

$$Y_t = \Pi X_t + V_t \quad (4)$$

Where Y_t and X_t are as defined in equation (3)

$\Pi = -\beta^{-1}\Gamma$ is unknown reduced form coefficients

$V_t = \beta^{-1}U_t$ is the matrix of reduced form disturbances.

Let us also define the following terms in addition to those in the nomenclature:

n = the number of stochastic equations in the model

n_1 = the number of endogenous (transformed and not transformed) variables included in the equation

h = total number of predetermined variables included in the equation.

Using zero restriction on the structural parameters, the necessary (order) condition for identification can be written as:

$$h - h_1 \geq n_1 - 1 \quad (5)$$

Equation (5) implies that the number of predetermined variables excluded from an equation must be at least as great as the number of endogenous variables included less one (Gujarati, 2005). This identification condition holds for just (exactly) identified equations if and only if:

$$h - h_1 = n_1 - 1 \quad (6)$$

And for over identified equations if and only if:

$$h - h_1 > n_1 - 1 \quad (7)$$

The structural equations of the non-linear model displayed in Table 1 shows that many variables are absent in each of the equations. Therefore, we use zero restrictions on the structural parameters as a way of examining the identification of the equations. Applying Equation (5) for order condition of identification for each of the equations in our model of study shows that all the equations in our model are over-identified.

Estimation

Since the model of Equation (1) has been identified using the conditions earlier established for this intrinsically linear model, we then conclude that the non-linear structural and reduced forms of Equations (3) and (4) are identical to the linear structural and reduced forms. For the purpose of estimation we normalize the equation in the model. The number of predetermined variables is greater than the number of sample points and also the number of stochastic equation is greater than the number of estimation period so that the three stage least square estimators among others is not applicable to this model (Johnston and Dinardo, 1997). We shall be using the ordinary least squares (OLS), two stage instrumental variable (2 SIV) and two stage principal component estimators in this study.

Ordinary least squares (OLS)

The variable normalized in each equation is regarded as the dependent variable and all other variables are regarded as independent variables in each equation. Equation (2) can be written as:

$$Y_1^0 = Z_i^0 \Gamma_i + U_i^0 \quad (8)$$

Where;

$$Z_i = [Y_i, X_i]$$

$$\Gamma_i = \begin{bmatrix} \beta_i \\ \alpha_i \end{bmatrix}$$

Applying OLS to Equation (8), we obtain the estimates of the structural parameters as:

$$\hat{\Gamma} = \left[Z_i^0 \; Z_i^0 \right]^{-1} \; Z_i^0 \; Y_i^0 \quad (9)$$

Instrumental variable method (IV)

The estimated correlation matrix of the predetermined variables X_i^0 in the non-linear model is used as the instruments in the first-stage regression. The variables that have the highest correlation with others are chosen and are regarded as being good representative of all the potential instruments following the arguments of Kelejian (1971) and Goldfield and Quandt (1972).

Table 1. Structural equation of the non-linear model.

Variables (₦m)	Stochastic equations
Gross domestic product in agriculture, current ($GDPA$)	$\alpha_1 + \alpha_2 \ \ EXAG_b + \alpha_3 \ \ PCOMP_t + \alpha_4 \ \ GDPA_t^* - 1 + \alpha_6 GFC_t$
Gross domestic product in mining and quarrying current, ($GDPMQ_t$)	$\alpha_6 + \alpha_7 + \alpha_8 \ GFC_t + \alpha_9 DI_t^*$
Gross domestic product in manufacturing, Current ($GDPM_t$)	$\alpha_{13} + \alpha_{14} GDPM_{t-1}^* + \alpha_{15} CEMET_t^* \ \alpha_{16}(CMMIPM + CHMIP)_t$
Gross domestic product in transport and communications, current ($GDPTC_t$)	$\alpha_{17} + \alpha_{18} GFC_t + \alpha_{19} GDPTC_{t-1}^*$
Gross domestic product in petroleum, current ($GDPP_t$)	$\alpha_{10} + \alpha_{11} ECP_t^* + \alpha_{12} CFLA_t^*$
Gross domestic product in construction materials, current ($GDPC_t$)	$\alpha_{20} + \alpha_{21} CFC_t^* + \alpha_{22} CMMIPM_t$
Gross domestic product in services, current ($GDPSVt$)	$\alpha_{23} + \alpha_{24}(PCOMP + GCOM)t + \alpha_{25} DI$
Import of machinery and transport equipment, current ($CHMIP_t$)	$\alpha_{63} + \alpha_{67} \ TME_t^* + \alpha_{68} \ SFR_{t-1}^* + \alpha_{69} \ TMI_t$
Import of construction materials, current ($CMMIPM_t$)	$\alpha_{70} + \alpha_{71} GDPC_t + \alpha_{72} CMMIPM * t$
Import of food, current ($In \ TMF_t$)	$\alpha_{59} + \alpha_{60} CFMET_t^* + \alpha_{61} DCOMP_t + \alpha_{62} PT_t^*$
Import tax revenue, current ($HITRP_t$)	$\alpha_{50} + \alpha_{51} TMI_t$
Government direct revenue, current (GDR_t)	$\alpha_{45} + \alpha_{46} GDPP_t$
Government other revenue, current ($InGORP_t$)	$\alpha_{47} + \alpha_{48} \ In \ TGDP_t + \alpha_{49} InT_t^*$
Rural population (million persons) ($RPOP_t$)	$\alpha_{38} + \alpha_{39} GDPA_t + \alpha_{40} T_t^*$
Urban population (million persons) ($UPOP_t$)	$\alpha_{41} + \alpha_{42} GDPSV_t + \alpha_{43} GDPM_t + \alpha_{44} POP_t$
Stock of foreign reserve, current (SFR_t)	$\alpha_{66} + \alpha_{67} \ TME_t^* + \alpha_{68} SFR_{t-1}^* + \alpha_{69} TMI_t$
Total current expenditure, current($In TME_t$)	$\alpha_{73} + \alpha_{74} \ InKF^* + \alpha_{75} \ InPXK \ _t^* + \alpha_{76} \ InTME \ _{t-1}^*$
Gross fixed capital formation (GFC_t)	$\alpha_{34} + \alpha_{35} TGDP_t + \alpha_{36}(CMMIPM + CHMIP)_t + \alpha_{37} DI_t$
Cost of living index ($InKX_t$)	$\alpha_{53} InTMS_t + \alpha_{54} InTCE_t + \alpha_{55} InFX_t^* + \alpha_{52}$
Private consumption expenditure, current $PCOMP_t$	$\alpha_{26} + \alpha_{27} GDR_T + \alpha_{28} PCOMP_{t-1}^* + \alpha_{29} DIN_t^*$
Government consumption expenditure, current ($InGCOM_t$)	$\alpha_{30} + \alpha_{31} LnTCR_t + \alpha_{32} InGCOM_{t-1}^* + \alpha_{33} \ In \ POP$

Table 1. Cont'd.

Total money supply (TMS_t)	$\alpha_{56}MB^{*}t+\alpha_{57}SFR_t+\alpha_{58}TMS^{*}_{t-1}$
Total government revenue, current ($In\ TCE_t$)	$\alpha_{77}+\alpha_{78}\ In\ TCRt$

Where* denotes predetermined variables and *In* is the log transformation (log specified equations).

the instruments are written as:

$$W_i^0=\left[X_i^0\ \ X_i^0\right] \tag{10}$$

And the 2SIV estimators of $\hat{\Gamma}_i=\begin{bmatrix}\beta_i\\ \gamma_i\end{bmatrix}$ is defined as:

$$\hat{\Gamma}_i=\begin{bmatrix}\beta_i\\ \gamma_i\end{bmatrix}=\left(W_i^0\,Z_i^0\right)-W_i^0\ Y_i^0 \tag{11}$$

For $Z_i^0=\left\{Y_i^0:X_i^0\right\}$

We considered six, eight and ten common instruments in turn, eight instruments performed best in terms of RMSE and Theils inequality and therefore, becomes the one chosen for this work.

Principal components (PC)

Principal component analysis is a process in which a group of correlated variables is reduced in number to a more fundamental set of orthogonal variables (Onyeagu, 2003).

The reduced set of variables is used, sometimes in a modified form in the first stage regression. This method is applied to the elements of Xt in Equation (3).

The performance of 2 SPC (two stage principal component) estimators vary with the numbers of PC used in the first stage regression. Following the works of Kelejian (1971), and Goldfield and Quandt (1972), we select the first 4, 6 and 8 principal components respectively to serve as the common instruments in each of the estimators. The principal components selected for each estimator becomes (Q*) which serve as initial instruments and the instruments of the first stage regression are;

$$S^0=\left(Q_j^{0*},X_i^0\right),\ j=1,2 \tag{12}$$

And the first stage of 2 SPC gives

$$\hat{Y}_i^0=S^0\left(S^{01}S^0\right)^{-1}S^{0'1}Y_i^0 \tag{13}$$

Thus the instruments are given as:

$$W_i=\left(Y_i^0,X_i^0\right) \tag{14}$$

Using the foregoing instruments for Equation (2), we get 2SPC estimates of $\Gamma_i=\begin{bmatrix}\beta\\ \alpha\end{bmatrix}$ of the parameters. In summary, the following five estimators are used for this work namely: ordinary least squares (OLS), eight instruments selected from the correlation matrix and any other predetermined variables that appear in the equation; ($2SIV_8$), first four principal component and any other predetermined variables that appear in the equation ($2SPC_4$), first six principal components and any other predetermined variables that appear in the equation; ($2SPC_6$) and first eight principal components and any other predetermined variables that appear in the equation ($2SPC_8$).

RESULTS AND DISCUSSION

The estimates of the structural parameters of the non-linear model are obtained using the five estimators thus stated. Tables 2 to 5 show for the five estimators, the root mean squares error (RMSE), Theils inequality coefficients, bias and variance proportions from the dynamic simulation. Thereafter, we use Friedman test statistics to rank the performances of the estimators with the four criteria listed and we obtain Table 6 which summaries the results.

The computed values summarized in Table 6 suggest that the five estimators have performed differently since from the statistical table $\chi^2_{0.001,4}=18.5$. We then re-rank the estimators based on the sum of their ranks (as indicated at the last row of each of Tables 2 to 5) and the results of this ranking are summarized in Table 7. From Table 7, it is seen in respect of this model and on the basis of the four criteria (bias, variance proportions, root mean square error and Theils inequality coefficient) that $2SPC_6$ and $2SPC_8$ emerged as the best estimators. However, from a closer comparison of the performances of these two estimators, one will be inclined to prefer $2SPC_6$, since not much improvement is achieved by increasing the components from Tables 6 to 7. The $2SIV_8$ closely follows $2SPC_8$ estimators in terms of performance. The least preferred estimators are the OLS and $2SPC_4$ in that order. The results also reveal that the performance of $2SIV_8$ demonstrated the importance of the correlation matrix in the selection of the instruments needed in the first stage regression. This result is not surprising because, the principal components are themselves based on the correlation matrix. It is interesting because of its simplicity as a method of selecting instruments. It is worthy of note that these findings which emerged in respect of Nigerian specific econometric models are in agreement with those of Goldfield and Quandt (1972), who concluded that these estimators

Table 2. The use of RMSE criterion to compare the estimators in the non-linear model.

Endogenous	OLS	$2S1V_8$	2 SPC_4	$2SPC_6$	$2SPC_8$
GDPA	(2) 476,5347	(1) 433.9790	(5) 2270.4205	(4) 491.4633	(3) 478.0918
GDPMQ	(3) 537,7392	(4) 564.3425	(5) 1887.7690	(1) 522.9112	(2) 535.2073
GDPMC	(4) 237,2330	(2) 236.3323	(3) 236.3964	(1) 234.8409	(5) 237.8533
GDPTC	(3) 84,9405	(5) 90.3718	(1) 78.5646	(2) 84.0402	(4) 87.0499
GDPC	(4) 126,0164	(1) 123.9190	(5) 126.1152	(3) 124.8253	(2) 124.7901
GDPSV	(3) 370,5594	(4) 377.9751	(5) 2306.2646	(1) 349.3577	(2) 353.8800
IMMG	(3) 149,7758	(4) 152.6250	(5) 256.6164	(1) 256.6164	(2) 149.1202
CMMIPM	(4) 43,5888	(1) 43.1809	(5) 43.6295	(2) 43.4641	(3) 43.5532
TMF	(4) 129,9472	(2) 129.2543	(5) 171.8170	(1) 129.1770	(3) 129.3835
GDR	(4) 310,7613	(3) 308.6691	(5) 2914.7857	(2) 308.6607	(1) 308.6579
GORP	(1) 443,4739	(4) 447.8391	(5) 638.8849	(3) 446.0477	(2) 444.5404
HITRP	(4) 85,5555	(3) 85.4099	(5) 94.7789	(1) 85.2264	(2) 85.3087
RPOP	(2) 0,4526	(1) 0.4513	(5) 0.5588	(3) 0.4556	(4) 0.45584
UPOP	(3) 0,2857	(1) 0.2700	(5) 1.3242	(2) 0.2814	(4) 0.2877
GFC	(4) 553.8781	(1) 540.8531	(5) 630.1481	(3) 546.4195	(2) 540.8832
POOMP	(3) 785, 8437	(4) 794.5445	(5) 5739.8618	(1) 781.0181	(2) 782.0522
GOOM	(4) 422, 7281	(3) 400.1625	(5) 1343.9839	(1) 379.7076	(2) 385.7180
KX	(5) 0, 17083	(4) 0.17077	(1) 0.1544	(2) 0.1630	(3) 0.1659
SFR	(1) 258, 2388	(4) 278.6448	(5) 388.8626	(3) 270.4811	(2) 269.3076
TMS	(1) 359.2280	(5) 377.4521	(4) 377.2053	(2) 268.4425	(2) 370.4422
TCE	(1) 2457,0500	(4) 2486.1532	(5) 2531.2593	(2) 2463.8473	(3) 2465.2425
Total ranks	63	61	94	41	55
New ranks	4	3	5	1	2

Table 3. The use of Theils inequality coefficients to compare estimators in the non-linear model.

Endogenous	OLS	$2S1V_8$	2 SPC_4	$2SPC_6$	$2SPC_8$
GDPA	(2.5) 0.0053	(1) 0.0044	(5) 0.1204	(4) 0.0056	(2.5) 0.0053
GDPMQ	(2.5) 0.0070	(4) 0.0078	(5) 0.0868	(1) 00.0067	(2.5) 0.0070
GDPMC	(3) 0.0091	(3) 0.00911	(3) 0.0091	(1) 0.0090	(5) 0.0092
GDPTC	(3).0.0069	(5) 0.0078	(1) 0.0059	(2) 0.0068	(4) 0.0072
GDPC	(3).0042	(1) 0.0041	(5) 0.0043	(3) 0.0042	(3) 0.0042
GDPSV	(3) 0.0021	(4) 0.0022	(5) 0.0802	(1) 0.0018	(2) 0.0019
IMMG	(3) 0.0098	(4) 0.0102	(5) 0.0288	(7) 0.0096	(2) 0.0097
CMMIPM	(5) 0.00371	(1) 0.0364	(3) 0.0037	(3) 0.0037	(3) 0.0037
TMF	(4) 0.0316	(2.5) 0.0313	(5) 0.0552	(1) 0.0312	(2.5) 0.0313
GDR	(4) 0.0096	(2) 0.0095	(5) 0.8440	(2) 0.0095	(2) 0.0095
GORP	(1) 0.0401	(4) 0.0409	(5) 0.0832	(3) 0.0406	(2) 0.0403
HITRP	(4) 0.0119	(2) 0.0118	(5) 0.01457	(2) 0.0118	(2) 0.0118
RPOP	(2.5) 0.00007	(2.5) 0.00007	(5) 0.00011	(2.5) 0.00007	(2.5) 0.00007
UPOP	(3.5) 0.00026	(1) 0.00023	(5) 0.00656	(2) 0.00025	(3.5) 0.00026
GFC	(4) 0.0076	(1.5) 0.0073	(5) 0.0099	(3) 0.0074	(1.5) 0.0073
POOMP	(3) 0.000182	(4) 0.0019	(5) 0.0969	(1.5) 0.0018	(1.5) 0.0018
GOOM	(4) 0.0209	(3) 0.0187	(5) 0.2112	(1) 0.0169	(2) 0.0174
KX	(4.5) 0.0157	(4.5) 0.0157	(1) 0.0128	(2) 0.0143	(3) 0.0148
SFR	(1) 0.0342	(4) 0.0399	(5) 0.0776	(3) 0.0376	(2) 0.0372
TMS	(1) 0.00579	(4) 0.0064	(5) 0.0065	(2) 0.0061	(3) 0.00616
TCE	(1) 0.1635	(4) 0.1673	(5) 0.1735	(2) 0.1644	(3) 0.1645
Total ranks	62.5	62	93	43	54.5
New ranks	4	3	5	1	2

Table 4. The use of bias proportion to compare the estimators in the non-linear model.

Endogenous	OLS	$2S1V_8$	2 SPC_4	$2SPC_6$	$2SPC_8$
GDPA	(1.5) 0. 00018	(1.5) 0. 00018	(5) 0.35192	(4) 0. 00030	(3) 0.00037
GDPMQ	(4) 0. 00017	(2) 5.156×10^{-6}	(5) 0. 42721	(3) 0. 00001	(1) 2.910×10^{-6}
GDPMC	(3) 4.66×10^{-6}	(2) 3.218×10^{-7}	(1)2.083×10^{-6}	(5) `0.00483	(4) 0.00005
GDPTC	(5) 0.00066	(2) 0.00023	(4) 0.00037	(3) 0.00032	(1) 0.00012
GDPC	(1) 0.00003	(5) 0.00023	(2) 0.00009	(4) 0. 00013	(3) 0.00011
GDPSV	(4) 0.0026	(3) 0. 00159	(5) 0.40089	(1) 0. 00132	(3) 0.00141
IMMG	(4) 0.00056	(3) 5.067×10^{-6}	(5) 0.29952	(1) 2.27×10^{-6}	(2) 3.277×10^{-6}
CMMIPM	(1) 0.00009	(5) 0.00109	(2) 0.00054	(4) 0.00068	(3) 0.00058
TMF	(2) 0.02703	(1) 0.02527	(5) 0.16143	(4) 0.02931	(3) 0.02831
GDR	(4) 0. 00080	(3)3.947×10^{-13}	(5) 0.43475	(1) 3.713×10^{-15}	(2)3.767×10^{-15}
GORP	(1) 0.00421	(2) 0.00579	(5) 0.17810	(4) 0.00632	(2) 0.00584
HITRP	(4) 0. 00244	(2) 0.00145	(5) 0.10007	(3) 0.00161	(1) 0.00155
RPOP	(4) 0.00005	(1) 3.027×10^{-6}	(5) 0.1234	(3) 6.23×10^{-6}	(2) 5.83×10^{-6}
UPOP	(1) 0.00003	(3) 0.00040	(5) 0. 37025	(4) 0.00367	(2) 0.00022
GFC	(4) 0.00021	(2) 0.00003	(5) 0.00032	(3) 0.00005	(2) 0.00002
POOMP	(4) 0.00063	(3) 0.00016	(5) 0.40083	(1) 0.00006	(3) 0.00008
GOOM	(1) 0.00612	(4) 0.00763	(5) 0.36884	(3) 0.00752	(2) 0.00751
KX	(1) 0.01948	(2) 0.04103	(5) 0.12628	(3) 0.04203	(4) 0.04254
SFR	(1) 0.00585	(4) 0.02086	(5) 0.21444	(3) 0.01868	(2) 0.0177
TMS	(1) 0.00010	(5) 0.00183	(4) 0.00143	(2) 0.00086	(3) 0.00108
TCE	(3) 0.04862	(4) 0.04993	(5) 0.16266	(1) 0.04676	(2) 0.04685
Total ranks	54.5	59.5	93	60	48
New ranks	2	3	5	4	1

Table 5. The use of variance proportion to compare the estimators in the non-linear model.

Endogenous	OLS	$2S1V_8$	2 SPC_4	$2SPC_6$	$2SPC_8$
GDPA	(4) 0.00073	(3) 0.00043	(5) 0.53319	(1) 3.35×10^{-8}	(2) 9.068×10^{-8}
GDPMQ	(4) 0.01897	(3) 0.01173	(5) 0.48841	(1) 0.00717	(2) 0.00855
GDPMC	(5) 0.01722	(2) 0.00933	(4) 0.01295	(1) 0.00004	(3) 0.00966
GDPTC	(1) 0.00004	(2) 0.00025	(4) 0.0037	(3) 0.00032	(1) 0.00012
GDPC	(5) 0.02039	(1) 0.00850	(4) 0.01355	(3) 0.01020	(2) 0.00906
GDPSV	(3) 0.00021	(4) 0.01024	(5) 0.54883	(1) 0.00002	(2) 0.00007
IMMG	(3) 0.00440	(4) 0.00446	(5) 0.37101	(1) 0.00230	(2) 0.00235
CMMIPM	(5) 0.06454	(1) 0.02656	(4) .040653	(3) 0.13252	(2) 0.002823
TMF	(4) 0.10862	(1) 0.10111	(5) 0.23549	(3) 0.10601	(2) 0.10599
GDR	(4) 0.02032	(3) 0. 00539	(5) 0.54165	(1) 0.00358	(2) 0.00416
GORP	(1) 0.03287	(2) 0.03973	(5) 0.19794	(3) 0.04240	(4) 0.04033
HITRP	(1) 0.01860	(3) 0.02481	(5) 0.06872	(4) 0.02608	(2) 0.02441
RPOP	(1) 0.00085	(2) 0.00186	(5) 0.12076	(4) 0.00231	(3) 0.00220
UPOP	(2) 0.00092	(4) 0.00979	(5) 0.43743	(1) 0.00026	(3) 0.00655
GFC	(4) 0.01014	(1) 0.00270	(5) 0.01330	(3) 0.00694	(2) 0.00427
POOMP	(1.5) 0.00016	(1.5) 0.00016	(5) 0.55570	(4) 0.00055	(3) 0.00042
GOOM	(3) 0. 00058	(4) 0.00061	(5) 0.51522	(1) 0.00003	(2) 0.00023
KX	(4) 0.03936	(1) 0.00282	(5) 0.21753	(3) 0.00689	(2) 0.00683
SFR	(1) 0.00043	(3) 0.01058	(5) 0.11065	(4) 0.01666	(2) 0.01023
TMS	(1)7.604×10^{-6}	(5) 0.00226	(4) 0.00100	(2) 0.0006	(4) 0.00130
TCE	(4) 0.34269	(5) 0.35076	(1) 0.01690	(2) 0.34001	(3) 0.34055
Total ranks	61.5	55.5	96	49	52
New ranks	4	3	5	1	2

Table 6. Summary of the Friedman test statistic values base on the estimators of the non- linear model.

Criteria	T-values	Decision
RMSE (Table 2)	26.42	Significant at 1%
Theils inequality Coefficient (Table 3)	26.16	Significant at 1%
Bias proportion (Table 4)	23.21	Significant at 1%
Variance proportion (Table 5)	26.56	Significant at 1%

Table 7. Summary of the ranks showing the relative performance of the five estimators based on the four criteria.

Criteria	Estimators listed in order of preference				
	$2SPC_6$	$2SPC_8$	$2SIV_8$	OLS	$2SPC_4$
Bias proportion	4	1	3	2	5
Variance proportion	1	2	3	4	5
RMSE	1	2	3	4	5
Thiels inequality coefficients	1(1)	2(2)	3(3)	4(4)	5(5)

(OLS, IV, 2SLS and 3SLS) do not rank differently in performances when used in estimating linear Models on one hand and intrinsically linear model on the other.

However, the findings are at variance with the works of Nehlawi (1977), which shows that OLS performs best in his family of the four estimators, OLS $2SPC_5$, $2SPC_8$ and PC, of the Canadian econometric model using simulation results.

Conclusion

From this study, we conclude that the identification of each equation in the intrinsically linear system follows almost the same procedures as in the case of the linear system, since all the non-linear variables are linearized by log transformation.

For the instrumental variable method employed in this study, since eight instruments performed best in terms of RMSE and Theils inequality, it was chosen for this work because the variables that have the highest correlation with others are chosen and are regarded as being good representative of all the potential instruments. The first 4, 6 and 8 principal components respectively were selected to serve as common instruments in each of the estimators. The five estimators performed differently using Friedman test statistic. Using the bias and variance proportions, RMSE and Theils inequality coefficient, ($2SPC_6$ and $2SPC_8$) emerged as the best estimators with a preference to $2SPC_6$, since not much improvement is achieved by increasing the component from 6 to 8. The least preferred estimators are the OLS and $2SPC_4$ in that order.

Nomenclature

₦m, Exogenous variables; **ECP,** export of crude petroleum, current; **CFLA**, capital formation in agriculture and mining; **CFC**, capital formation in construction materials; **CFMET**, capital formation in machinery and transport equipment, current; EXAG, export of agricultural products, current; **FEL**, level of foreign exchange; current; **FX**, import price index; **MB**, high powered money, current; DIN, national disposable income, current; T, time measured in years; **PT**, terms of trade (PXK/FX); **D1**, dummy variable; **PXK**, export price index; **TMS,** money supply; **TGDP,** total gross domestic product, current; **TCR**, total government revenue, current; **KF** = EXAG + ECP; **XX** = CMMIPM + $CHMIP_t$; **XG** = PCOMP + GCOM; **POP** **=** RPOP + UPOP; **TMI** = IMMG + CHMIP + CMMIPM + TMF; **TCR** = GDR + HITRP + GORP; **TGDP** = GDPA + GDPMQ + GDPM + GDPTC + GDPC + GDPASV.

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