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ORIGINAL STUDY

Comparative Evaluation of Estimation Techniques for Purchasing Power Parity in African Countries Using the Country-Product-Dummy Regression Framework

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Abstract

Purchasing Power Parity (PPP) is a popular macroeconomic analysis metric used to compare economic productivity and standards of living between countries. This study examines the estimation of PPP within the International Comparison Program (ICP) at Basic Heading (BH) level stage and leverages on the data from the 2011 ICP round. Focusing on five BHs out of 12 BHs across 50 Africa countries, to empirically evaluate the validity of the classical Ordinary Least Square (OLS) assumptions in the estimation of Country Product Dummy (CPD) regressions. Given the widespread use of OLS for BH level PPP computation, a rigorous examination of these assumptions is essential to ensuring the statistical reliability of PPP estimates. For the five BHs considered, it was observed that the problem of Heteroscedasticity and Non-Normality is common to all the BHs while one of the BH also has the problem of Auto-correlation inclusive. The Generalized Least Square (GLS), Robust standard error, Quantile Regression, and Box-Cox was used to address the problem detected. To evaluate the precision of estimate and model fit performance, standard error and residual standard error was used as criteria respectively. For the estimate precision, Quantile regression has the least value of standard error across all the BHs and GLS also has the least value for residual standard error across all the BHs for model fitting.

Keywords: Country Product Dummy, OLS, Regression, Estimates, Purchasing power parity, Basic Heading

1. Introduction

Purchasing Power Parities (PPPs) represent a fundamental macroeconomic concept which posits that the exchange rate between two currencies should equate to the ratio of their respective price levels for a comparable basket of goods and services. Essentially, PPP theory asserts that, when expressed in a common currency identical goods and services should have equivalent prices across countries. As a cornerstone of international economic comparisons, PPPs enable the adjustment of national accounts to account for disparities in price levels and currency values among countries. These estimates are systematically produced through the International Comparison Program (ICP) a global statistical initiative led by the World Bank, under the supervision of the United Nations Statistical Commission, and implemented in collaboration with regional partners such as the Organisation for Economic Co-operation and Development (OECD) and Eurostat, the statistical office of the European Union [1,2].

The ICP methodology relies on detailed national-level price and expenditure data, by employing a suite of index number formulas to derive PPPs and

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real expenditures. However, despite the methodological rigor, a key limitation of the ICP is its omission of statistical reliability measures such as standard errors or confidence intervals for estimated PPPs and derived aggregates. This lack of inferential metrics restricts the ability to formally assess the precision and robustness of the results [3].

Historically, the construction of price indices has evolved through several conceptual frameworks. The stochastic approach, with roots in the works of Jevons, Edgeworth, Bowley, and Fisher, models price indices as outcomes of statistical estimation [4]. Although the axiomatic and economic-theoretic approaches dominated much of the 20th century, interest in the stochastic perspective was revitalized by contributions from Refs. [5–8].

A significant advancement within the stochastic framework of international price comparisons is the Country-Product-Dummy (CPD) model, originally proposed by Ref. [9]. Initially developed for imputing missing price observations and estimating PPPs at the Basic Heading (BH) level, the CPD model has since evolved into a versatile instrument with broader applications. Subsequent research [10–17] has expanded the CPD framework, establishing its theoretical equivalence to various classical index number formulas and demonstrating its suitability for both bilateral and multilateral price comparisons. As highlighted by Ref. [18], the CPD model now serves as a robust and adaptable tool in the measurement of international price levels, offering both methodological rigor and practical utility in the context of global statistical initiatives such as the ICP.

While the CPD model is widely recognized for its integration of regression-based estimation techniques, a critical yet underexplored issue persists in the literature. Specifically, the model's implementation in PPP computation below the BH level typically relies on Ordinary Least Squares (OLS) estimation. This econometric foundation is often praised for enabling the calculation of standard errors a methodological advantage rarely attainable within traditional ICP aggregation approaches [14]. However, despite this strength, a fundamental concern remains largely unaddressed: the diagnosis and verification of the Gauss–Markov assumptions underpinning the validity of OLS estimates. In the absence of these assumptions such as homoscedasticity, no autocorrelation, no multicollinearity, non-normality and correct model specification, the OLS estimator ceases to be the Best Linear Unbiased Estimator (BLUE), thus jeopardizing the reliability of derived PPPs. Recent econometric literature [19] underscores that violations of these assumptions can result in biased, inefficient, or inconsistent estimates, yet many empirical applications of the CPD model proceed without formally testing or correcting for such violations. This oversight represents a significant methodological gap in the current practice of PPP computation, warranting closer scrutiny and robust diagnostic procedures.

This study investigates the often-overlooked issue of whether the classical OLS assumptions hold in CPD regressions used for computing PPPs. Using 2011 ICP data across five Basic Headings and 50 African countries, it evaluates the validity of assumptions such as homoscedasticity and model specification. The study emphasizes the importance of diagnostic testing to ensure the statistical reliability and precision of PPP estimates derived through OLS.

2. Methodology

The methodology for computing PPPs within the ICP is a multi-layered process designed to ensure comparability of real expenditures across countries. Detailed discussions of the ICP framework can be found in Refs. [1,20]. The computation of PPPs generally follows a two-stage procedure, reflecting both the structure of available data and the principles of index number theory.

2.1. First stage: basic heading-level estimation

In the first stage, national average prices for individual items are aggregated to produce BH-level PPPs. This stage is analogous to the construction of elementary indices in the context of Consumer Price Indices (CPI), where no expenditure weights are applied. The ICP typically employs unweighted multilateral index number methods at this level, most notably the Country-Product-Dummy (CPD) model and the Gini–Éltető–Köves–Szulc (GEKS) method [21].

The CPD model, originally introduced by Ref. [9], is widely used in the ICP implementation by the World Bank, while the OECD–Eurostat regional program predominantly uses the GEKS method. The basic heading level represents the lowest level of aggregation for which both price and expenditure data are collected and reported by Ref. [4].

2.2. Second stage: aggregation to higher levels

In the second stage, PPPs computed at the basic heading level are aggregated to higher levels of national accounts, such as main aggregates and Gross Domestic Product (GDP). This aggregation is expenditure-weighted, reflecting the relative importance of each basic heading in a country's consumption basket.

Several methods are available for this second-stage aggregation, including the GEKS, weighted CPD, Geary–Khamis (GK), and Iklé methods [22]. Among these, the GEKS method is preferred in both the World Bank and OECD–Eurostat implementations due to its transitivity and multilateral comparability properties. However, in cases where additivity is required i.e., where real expenditures must sum consistently across aggregation levels the GK and Iklé methods are employed, despite known trade-offs such as potential substitution bias [4].

2.3. Country Product Dummy (CPD) purchasing power parities

Country Product Dummy (CPD) is the main methods used by the ICP at the World Bank. It was developed by Ref. [9], CPD has the ability to deal with data issues arising from the quality variation of item across areas and to fill gaps in available price data for making PPP comparison. The CPD PPPs are estimated from the following equation:

$$\ln P_{ij} = \pi_1 D_1 + \pi_2 D_2 + \ldots + \pi_M D_M + \mu_1 D_1^* + \mu_2 D_2^* + \ldots + \mu_N D_N^* + \varepsilon_{ij} \quad (1)$$

Where: $i = 1, 2, \ldots N\ (Product)\ and\ j = 1, 2, \ldots M\ (Countries)$

$D_i\ and\ D_j^*$ are product and country dummy variables which take value 1 for commodity i and country j respectively and 0 otherwise where ε_{ij} is the random disturbance terms which are independent and identically distributed, i.e $\varepsilon_{ij} \sim N(0, \sigma^2)$ [4].

Equation (1) can be expressed for each basic heading as:

$$\ln p_{ij} = \sum_{j=1}^{M} \pi_j D_j + \sum_{i=1}^{N} \mu_i D_i^* + \varepsilon_{ij} \quad (2)$$

Where $\mu_i\ and\ \pi_j$ are the coefficient of product i and country j respectively.

Setting $\pi_M = 0$ implies that the currency of country M is the numeraire or reference with

$PPP_M = 1$, the remaining parameters can be estimated.

The μ_i and π_j in the CPD model are typically estimated using Ordinary Least Squares (OLS). Under the classical Gauss–Markov assumptions, the OLS estimator retains its desirable properties, notably being the Best Linear Unbiased Estimator (BLUE).

Once the regression model is successfully estimated, the PPP for country j under BH h can be derived from the country effect parameter α_j as follows:

$$PPP_j^h = Exp(\alpha_j) = e^{\alpha_j} \quad (3)$$

2.3.1. Assumption of OLS and its remedial

When using Ordinary Least Squares (OLS) in other to estimate the CPD model, it's important to understand the classical linear regression assumptions that ensure the estimator is BLUE (Best Linear Unbiased Estimator). Violations of these assumptions may lead to biased, inefficient, or invalid inference. Below are some key assumptions and common remedial measures:

1. Multicollinearity: Independent variables (dummies in CPD) are not perfectly correlated.
2. Homoscedasticity: The variance of error term is constant across observations; $Var[\varepsilon_{ij}] = \sigma^2$
3. No autocorrelation: Error terms are uncorrelated across observations
4. Normality: Errors are normally distributed [23]

Remedial Measures

1. For multicollinearity we can remove the variables that are correlated or use Principal Component Analysis (PCA), Ridge regression, Liu regression etc.
2. Homoscedasticity: apply Weighted Least Square, Generalized Least Square (GLS), Robust Standard Errors or Long transformation
3. Autocorrelation: apply Generalized Least Square (GLS)
4. Normality: transform dependent variable or use non parametric method
5. Quantile regression is more robust to non-normality, heteroscedasticity and outliers
6. Box Cox is used to handle non-normality and heteroscedasticity in residual.

2.3.2. Generalized Least Squares (GLS)

Generalized Least Squares (GLS) is a technique used to estimate the parameters of a regression model when the assumptions of Ordinary Least Squares (OLS) are violated, especially when there is heteroscedasticity (non-constant variance) or autocorrelation (correlated residuals). Unlike OLS, which assumes constant variance (homoscedasticity) and no correlation between the residuals, GLS accounts for these violations by modeling the covariance structure of the error terms. This leads to more efficient parameter estimates under such conditions. The GLS estimator can be expressed as:

$$\widehat{\beta}_{GLS} = \left(X^T\Omega^{-1}X\right)^{-1}X^T\Omega^{-1}Y \tag{4}$$

Where: X is the matrix of explanatory variables (independent variables), Y is the vector of observed values (dependent variable), Ω is the covariance matrix of the residuals, Ω^{-1} is the inverse of the covariance matrix [24].

2.3.3. Box-Cox transformation

The Box-Cox transformation is a family of power transformations applied to data to stabilize variance and make the distribution more normal. This transformation can address issues such as skewness in the data, which often occurs in heteroscedastic datasets. The transformation is defined as:

$$Y(\lambda) = \begin{cases} \dfrac{y^\lambda - 1}{\lambda}, if\ \lambda \neq 0 \\ \log(y), if\ \lambda = 0 \end{cases} \tag{5}$$

Where λ is the transformation parameter, and the transformation adjusts the data based on its value. If λ = 0, the Box-Cox transformation reduces to a natural logarithm transformation. The optimal λ is estimated using maximum likelihood estimation to improve the normality of the data [25].

2.3.4. Quantile Regression

Quantile Regression estimates the conditional quantiles of the dependent variable, rather than the conditional mean, which makes it robust to outliers and skewed distributions. It allows us to model the relationship between the dependent and independent variables at different quantiles (e.g., 0.25, 0.5, 0.75), providing a more complete picture of the data. The quantile regression method makes no assumptions about the distribution of the error term and is robust to heteroscedasticity and outliers and is estimated by minimizing the following objective function:

$$\widehat{\beta}_{(\tau)} = argmin_\beta \sum_{i=1}^{n} \rho_\tau\left(y_i - x_i^T\beta\right) \tag{6}$$

where:

$\rho_\tau(u) = u(\tau - \mathrm{I}(u < 0))$ is the check function, τ represents the quantile (e.g., τ = 0.5 for the median), y_i is the observed value for the dependent variable, $x_i^T\beta$ is the predicted value for the independent variables [26,27].

2.3.5. Robust Standard Errors

Robust Standard Errors are used in regression models when the assumption of homoscedasticity (constant variance of residuals) is violated. Traditional OLS standard errors assume that the residuals have constant variance, but this assumption may be unrealistic in the presence of heteroscedasticity. Robust standard errors adjust for this by providing consistent estimates of the standard errors, even when the errors are heteroscedastic. The formula for robust standard errors is:

$$SE\_robust = \sqrt{\widehat{\sigma}^2\left(X^TX\right)^{-1}} \tag{7}$$

where:

$\widehat{\sigma}^2 = \frac{1}{n-p}\sum_{i=1}^{n} e_i^2$ is the heteroscedasticity-consistent estimate of the variance of residuals e_i, X^TX is the matrix of explanatory variables, and

p is the number of predictors (including the intercept) [28].

2.4. Criteria for choosing the best estimators

Residual standard error and standard error were the criteria used to select the best model fit in this study.

2.4.1. Residual Standard Error (RSE)

The Residual Standard Error measures the typical size of the residuals that is, the typical distance between the observed data points and the model's predicted values in a regression model. It indicates how well the model fits the data. Lower RSE implies a better model fit.

$$RSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2}{n-p}} \tag{8}$$

Where:

y_i = observed values, $\widehat{y}$ = predicted values, n = number of observations,

p = number of estimated parameters (including the intercept)

2.4.2. Standard Error (SE)

Standard Error refers to the standard deviation of an estimated parameter. In regression, the SE is typically reported for each coefficient estimate, such as the intercept or slope. It tells how precise coefficient estimate is, the smaller SEs suggest a more precise estimates.

$$SE(\widehat{\beta}) = \sqrt{\frac{\sigma^2}{\sum (x_i - \overline{x})^2}} \tag{9}$$

3. Results and discussion

The ICP dataset 2011 which consists of twelve (12) BHs out of which five (5) BHs was used in this study namely: Food and Non-alcoholic beverages (BH1), Alcoholic beverages, narcotic, and tobacco (BH2), Clothing and footwear (BH3), Household goods and services (BH5), and Transport (BH7) respectively. OLS assumption was carried out on the 5 BHs using R-statistical software 4.4.2 version for the computation, libraries (dplyr, tidyr, nlme, MASS, quantreg and tibble). Below are the results outputs of the OLS assumptions.

3.1. BH1 CPD regression diagnostics

Breusch-Pagan Test for Heteroscedasticity: model BP = 231.1, df = 77, p-value = 2.2e-16
Shapiro-Wilk Test for Normality of Residuals: W = 0.99062, p-value = 5.784e-08
Durbin-Watson Test for Autocorrelation: Model DW = 2.0625, p-value = 0.6705
Variance Inflation Factor (VIF): GVIF Df GVIF^(1/(2*Df))

Country 1.006962 49 1.000071
Product 1.006962 28 1.000124

From the above results, the problem of Heteroscedasticity and Non-Normality of residual is detected because both p-values are lesser than alpha 0.05. No multicollinearity since the GVIF is lesser than 10 and no presence of autocorrelation was detected.

3.2. BH2 CPD regression diagnostics

Breusch-Pagan Test for Heteroscedasticity: model BP = 81.755, df = 53, p-value = 0.006811
Shapiro-Wilk Test for Normality of Residuals: W = 0.98458, p-value = 0.01792
Durbin-Watson Test for Autocorrelation: model DW = 2.2734, p-value = 0.9425
Variance Inflation Factor (VIF): GVIF Df GVIF^(1/(2*Df))

Country 1.154708 49 1.001469
Product 1.154708 4 1.018144

From the above results, the problem of Heteroscedasticity and Non-Normality of residual is detected because both p-values are lesser than alpha 0.05. No multicollinearity since the GVIF is lesser than 10 and no presence of autocorrelation was detected.

3.3. BH3 CPD regression diagnostics

Breusch-Pagan Test for Heteroscedasticity: model BP = 106.44, df = 53, p-value = 1.889e-05
Shapiro-Wilk Test for Normality of Residuals: model W = 0.98349, p-value = 0.005488
Durbin-Watson Test for Autocorrelation: model DW = 1.771, p-value = 0.03188
Variance Inflation Factor (VIF): GVIF Df GVIF^(1/(2*Df))

Country 1.004016 49 1.000041
Product 1.004016 4 1.000501

From the above results, the problem of Heteroscedasticity, Non-Normality and autocorrelation of residual were detected because their p-values are lesser than alpha 0.05. No multicollinearity since the GVIF is lesser than 10.

3.4. BH5 CPD regression diagnostics

Breusch-Pagan Test for Heteroscedasticity: model BP = 199.24, df = 61, p-value = 2.2e-16
Shapiro-Wilk Test for Normality of Residuals: model W = 0.97711, p-value = 3.77e-08
Durbin-Watson Test for Autocorrelation: model DW = 2.0525, p-value = 0.5619
Variance Inflation Factor (VIF): GVIF Df GVIF^(1/(2*Df))

Country 1.070754 49 1.000698
Product 1.070754 12 1.002853

From the above results, the problem of Heteroscedasticity and Non-Normality of residual are present. No multicollinearity since the GVIF is lesser than 10 and no presence of autocorrelation was detected.

3.5. BH7 CPD regression diagnostics

Breusch-Pagan Test for Heteroscedasticity: model BP = 108.32, df = 58, p-value = 6.883e-05
Shapiro-Wilk Test for Normality of Residuals: model W = 0.98906, p-value = 0.002896
Durbin-Watson Test for Autocorrelation: model DW = 2.114, p-value = 0.7606
Variance Inflation Factor (VIF): GVIF Df GVIF^(1/(2*Df))

Country 1.185721 49 1.001740
Product 1.185721 9 1.009509

From the above results, the problem of Heteroscedasticity and Non-Normality of residual are present. No multicollinearity since the VIF is lesser than 10 and no autocorrelation was presence.

Since some of the assumptions of OLS was violated in all the BHs, GLS, Robust standard error, Quantile and Box & Cox estimators was used to address those problems detected at each BH. Tables 1–5 gives the estimates for different estimators used at each basic heading for 50 Africa countries where Nigeria is used as reference country.

Table 1 present the results for BH1 (Food and Non-alcoholic Beverages), since there exist a problem of heteroscedasticity and non-normality, GLS and Robust standard error is used to correct the

Table 1. Estimate of PPP for different estimators under BH1 using Nigeria as ref. country.

S/NO	Country	OLS	GLS	Box Cox	Robust	Quantile
1	AGO (Angola)	0.7797	0.7836	0.7972	0.7799	0.7689
2	BDI (Burundi)	7.3558	7.3264	12.1025	7.2341	7.3719
3	BEN (Benin)	2.6672	2.6611	2.9883	2.6916	2.7187
4	BFA (Burkina Faso)	2.874	2.8721	3.2667	2.8474	2.9949
5	BWA (Botswana)	0.0457	0.0456	0.1006	0.0452	0.0446
6	CAF (Central Africa Republic)	3.6818	3.6724	4.5134	3.7039	3.6433
7	CIV (Côte d'Ivoire)	3.0667	3.0605	3.5505	3.0845	3.0483
8	CMR (Cameroon)	2.9015	2.8921	3.3339	2.9348	2.9012
9	COD (Congo, Dem. Rep.)	7.6251	7.6057	12.4608	7.5253	7.4977
10	COG (Congo)	3.7277	3.7194	4.5436	3.7056	3.7162
11	COM (Comoros)	2.7037	2.6934	3.06	2.6217	2.5732
12	CPV (Cabo Verde)	0.4861	0.4844	0.5151	0.4866	0.4968
13	DJI (Djibouti)	1.1465	1.1373	1.1735	1.0823	1.0762
14	DZA (Algeria)	0.3414	0.3408	0.3871	0.3262	0.3147
15	EGY (Egypt)	0.023	0.023	0.0718	0.0216	0.0207
16	ETH (Ethiopia)	0.0659	0.0658	0.1239	0.0666	0.0632
17	GAB (Gabon)	4.552	4.5418	6.0058	4.3864	4.224
18	GHA (Ghana)	0.011	0.011	0.0514	0.011	0.0107
19	GIN (Guinea)	37.8823	37.7992	213.1329	37.9813	35.5958
20	GMB (Gambia)	0.1423	0.1419	0.1998	0.1442	0.1467
21	GNB (Guinea-Bissau)	2.942	2.9363	3.3705	2.9178	2.8493
22	GNQ (Equatorial Guinea)	3.892	3.888	4.8822	3.8206	3.7439
23	KEN (Kenya)	0.4067	0.4058	0.4417	0.4041	0.4009
24	LBR (Liberia)	0.0066	0.0066	0.0422	0.0065	0.0064
25	LSO (Lesotho)	0.0431	0.043	0.0975	0.0428	0.042
26	MAR (Morocco)	0.0476	0.0475	0.1033	0.046	0.0454
27	MDG (Madagascar)	8.4667	8.4477	14.6439	8.5024	7.777
28	MLI (Mali)	2.6166	2.6167	2.9122	2.6018	2.6404
29	MOZ (Mozambique)	0.1869	0.1865	0.2426	0.1857	0.1821
30	MRT (Mauritania)	1.2757	1.2806	1.2909	1.2581	1.2517
31	MUS (Mauritius)	0.184	0.1837	0.2402	0.1779	0.1693
32	MWI (Malawi)	0.9487	0.9497	0.9632	0.9336	0.9309
33	NAM (Namibia)	0.0554	0.0552	0.1116	0.0546	0.0528
34	NER (Niger)	3.0024	2.9952	3.4529	2.9679	2.9466
35	RWA (Rwanda)	3.3088	3.2974	3.9601	3.4069	3.449
36	SDN (Sudan)	0.0151	0.0151	0.0591	0.0148	0.014
37	SEN (Senegal)	2.7922	2.7899	3.1543	2.7678	2.6207
38	SLE (Sierra Leone)	23.2367	23.1886	81.4828	23.1866	23.4724
39	STP (São Tomé and Principe)	121.4989	121.2031	3246.686	120.3454	117.6697
40	SWZ (Eswatini)	0.0413	0.0412	0.0953	0.0409	0.0403
41	SYC (Seychelles)	0.0809	0.0807	0.1399	0.0776	0.0733
42	TCD (Chad)	3.0509	3.0433	3.5181	3.0514	2.9651
43	TGO (Togo)	2.9169	2.9109	3.3271	2.9039	2.8376
44	TUN (Tunisia)	0.0073	0.0073	0.044	0.0071	0.0068
45	TZA (Tanzania)	6.9042	6.8879	10.7429	6.862	6.7369
46	UGA (Uganda)	11.4098	11.3779	23.5159	11.5558	11.4336
47	ZAF (South Africa)	0.0475	0.0474	0.1028	0.0461	0.044
48	ZMB (Zambia)	28.5056	28.4385	120.4631	28.6534	26.9304
49	ZWE (Zimbabwe)	0.0059	0.0059	0.0406	0.006	0.0058

Table 2. Estimate of PPP for different estimators under BH2 using Nigeria as ref. country.

S/NO	Country	OLS	GLS	Box Cox	Robust	Quantile
1	AGO (Angola)	0.6261	0.6288	0.6396	0.6214	0.5705
2	BDI (Burundi)	9.0203	9.3713	15.9755	9.5176	9.428
3	BEN (Benin)	2.7426	2.8313	3.0726	2.9964	3.3201
4	BFA (Burkina Faso)	2.8463	2.9017	3.2223	2.938	2.9541
5	BWA (Botswana)	0.0682	0.0707	0.1277	0.064	0.0633
6	CAF (Central Africa Republic)	3.8457	3.9461	4.7256	4.1898	4.3847
7	CIV (Côte d'Ivoire)	3.1135	3.1578	3.6276	3.2138	3.2175
8	CMR (Cameroon)	3.0626	3.1011	3.5642	3.1612	3.0684
9	COD (Congo, Dem. Rep.)	9.1008	9.286	16.2047	9.3939	9.5459
10	COG (Congo)	3.5686	3.6324	4.3053	3.6836	3.6022
11	COM (Comoros)	4.7994	4.9797	6.3516	5.0608	4.6824
12	CPV (Cabo Verde)	0.6709	0.7039	0.6899	0.6899	0.7354
13	DJI (Djibouti)	1.3588	1.4137	1.4068	1.561	1.8074
14	DZA (Algeria)	0.6123	0.6475	0.6414	0.6719	0.7836
15	EGY (Egypt)	0.0383	0.0395	0.0878	0.0397	0.0394
16	ETH (Ethiopia)	0.1015	0.104	0.1619	0.0984	0.0848
17	GAB (Gabon)	3.4893	3.5602	4.1831	3.4462	3.3842
18	GHA (Ghana)	0.0108	0.0111	0.0512	0.0112	0.0114
19	GIN (Guinea)	42.5078	43.4962	272.3654	45.6936	43.7432
20	GMB (Gambia)	0.1666	0.1687	0.2223	0.1746	0.175
21	GNB (Guinea-Bissau)	3.4863	3.5818	4.1523	3.6995	3.8619
22	GNQ (Equatorial Guinea)	3.7828	3.8779	4.6764	3.6345	3.8011
23	KEN (Kenya)	0.7296	0.7347	0.7464	0.6815	0.6465
24	LBR (Liberia)	0.0073	0.0075	0.044	0.0084	0.0089
25	LSO (Lesotho)	0.0571	0.0593	0.1157	0.051	0.0536
26	MAR (Morocco)	0.0934	0.0966	0.153	0.0967	0.0957
27	MDG (Madagascar)	10.1543	10.3868	19.3492	10.9681	11.4311
28	MLI (Mali)	2.7957	2.8962	3.1906	2.4604	2.2598
29	MOZ (Mozambique)	0.2073	0.2131	0.2601	0.2132	0.2076
30	MRT (Mauritania)	2.127	2.1756	2.3512	2.2311	1.6353
31	MUS (Mauritius)	0.2965	0.3117	0.3534	0.2659	0.348
32	MWI (Malawi)	1.0811	1.112	1.0914	1.1227	1.216
33	NAM (Namibia)	0.0631	0.0653	0.1221	0.0551	0.0501
34	NER (Niger)	3.3139	3.3895	3.896	3.4206	3.3471
35	RWA (Rwanda)	5.4478	5.6816	7.6031	5.3439	4.3848
36	SDN (Sudan)	0.0329	0.0344	0.0784	0.0345	0.0335
37	SEN (Senegal)	3.7986	3.8672	4.7053	3.8745	3.9483
38	SLE (Sierra Leone)	23.2734	23.798	81.2324	24.7771	29.5398
39	STP (São Tomé and Principe)	142.2475	146.1806	5024.776	146.2884	130.8821
40	SWZ (Eswatini)	0.0578	0.0599	0.1164	0.0504	0.0509
41	SYC (Seychelles)	0.1938	0.2018	0.2532	0.1769	0.1968
42	TCD (Chad)	4.0179	4.0776	5.0529	4.0362	3.8641
43	TGO (Togo)	2.9573	3.0015	3.3917	3.0526	3.1056
44	TUN (Tunisia)	0.0137	0.0142	0.0567	0.0131	0.0152
45	TZA (Tanzania)	9.9171	10.2133	18.6361	10.1988	10.9129
46	UGA (Uganda)	17.7297	18.3284	49.0719	17.9174	15.9154
47	ZAF (South Africa)	0.061	0.0629	0.1191	0.0562	0.056
48	ZMB (Zambia)	44.2138	45.6631	294.751	49.1111	45.8813
49	ZWE (Zimbabwe)	0.006	0.0062	0.0406	0.0062	0.0066

problem of heteroscedasticity, Quantile is used for non-normality while Box Cox is used for both heteroscedasticity and non-normality.

Table 2 shows the results for BH2 (Alcoholic beverages, tobacco, narcotics), since there exist a problem of heteroscedasticity and non-normality, GLS and Robust standard error is used to correct the problem of heteroscedasticity, Quantile is used for non-normality while Box Cox is used for both heteroscedasticity and non-normality.

Table 3 present the results for BH3 (Clothing and footwears), the problem of Heteroscedasticity, Non-Normality and Autocorrelation of residual were detected. Robust standard error is used to correct the problem of heteroscedasticity, GLS can handle both Autocorrelation and Heteroscedasticity. Quantile is used for non-normality while Box Cox is used for both heteroscedasticity and non-normality.

Table 4 shows the results for BH5 (Household goods and services), since there exist a problem of

Table 3. Estimate of PPP for different estimators under BH3 using Nigeria as ref. country.

S/NO	Country	OLS	GLS	Box Cox	Robust	Quantile
1	AGO (Angola)	1.4078	1.4078	1.4165	1.4067	1.3756
2	BDI (Burundi)	6.1359	6.1359	8.9412	6.1359	5.9916
3	BEN (Benin)	3.3842	3.3842	3.9883	3.3554	3.0813
4	BFA (Burkina Faso)	2.8931	2.8931	3.2893	2.8931	2.5408
5	BWA (Botswana)	0.063	0.063	0.1198	0.0609	0.0568
6	CAF (Central Africa Republic)	3.2428	3.2428	3.792	3.2428	3.3587
7	CIV (Côte d'Ivoire)	4.0677	4.0677	5.0749	4.0836	3.8984
8	CMR (Cameroon)	4.4375	4.4375	5.6753	4.4375	4.3343
9	COD (Congo, Dem. Rep.)	7.4138	7.4138	11.7859	7.4138	6.9576
10	COG (Congo)	4.7981	4.7981	6.3229	4.7981	4.5238
11	COM (Comoros)	3.9396	3.9396	4.878	3.7029	3.4246
12	CPV (Cabo Verde)	0.8362	0.8362	0.8435	0.8362	0.7715
13	DJI (Djibouti)	1.6324	1.6324	1.7006	1.561	1.4439
14	DZA (Algeria)	0.6338	0.6338	0.6486	0.6451	0.5966
15	EGY (Egypt)	0.0241	0.0241	0.0729	0.0229	0.0206
16	ETH (Ethiopia)	0.0828	0.0828	0.1413	0.0828	0.0777
17	GAB (Gabon)	5.3667	5.3667	7.3764	5.3667	5.1948
18	GHA (Ghana)	0.0101	0.0101	0.0495	0.0101	0.0098
19	GIN (Guinea)	28.986	28.9861	124.0075	30.1256	31.9561
20	GMB (Gambia)	0.116	0.116	0.1741	0.116	0.1076
21	GNB (Guinea-Bissau)	4.2295	4.2295	5.3357	4.1631	3.9811
22	GNQ (Equatorial Guinea)	4.6836	4.6836	6.3226	5.4578	5.6025
23	KEN (Kenya)	0.4772	0.4772	0.5028	0.4772	0.4654
24	LBR (Liberia)	0.0067	0.0067	0.0425	0.007	0.0065
25	LSO (Lesotho)	0.0682	0.0682	0.1256	0.0661	0.0639
26	MAR (Morocco)	0.0657	0.0657	0.1227	0.065	0.0615
27	MDG (Madagascar)	7.7117	7.7117	12.5194	7.7117	7.2768
28	MLI (Mali)	3.2661	3.2661	3.8356	3.2791	3.3178
29	MOZ (Mozambique)	0.223	0.223	0.274	0.237	0.2357
30	MRT (Mauritania)	1.3489	1.3489	1.3629	1.3489	1.2978
31	MUS (Mauritius)	0.2867	0.2867	0.3331	0.2615	0.2382
32	MWI (Malawi)	1.0629	1.0629	1.0652	1.0357	0.9213
33	NAM (Namibia)	0.0761	0.0761	0.135	0.0698	0.0686
34	NER (Niger)	2.6058	2.6058	2.8912	2.603	2.4383
35	RWA (Rwanda)	3.7507	3.7507	4.6161	3.9862	4.3166
36	SDN (Sudan)	0.0163	0.0163	0.0608	0.0165	0.0177
37	SEN (Senegal)	3.3634	3.3634	3.9521	3.3634	3.2468
38	SLE (Sierra Leone)	18.249	18.2492	51.5141	18.2492	17.6869
39	STP (São Tomé and Principe)	160.77	160.7712	6752.215	159.7632	153.3194
40	SWZ (Eswatini)	0.0723	0.0723	0.1297	0.0723	0.0677
41	SYC (Seychelles)	0.1416	0.1416	0.1987	0.1365	0.1372
42	TCD (Chad)	3.447	3.447	4.0924	3.447	3.2875
43	TGO (Togo)	2.9131	2.9131	3.3182	2.8962	2.8732
44	TUN (Tunisia)	0.0151	0.0151	0.0588	0.0149	0.0145
45	TZA (Tanzania)	7.0566	7.0566	10.9518	7.0566	6.6891
46	UGA (Uganda)	12.539	12.539	27.1607	12.3817	11.7397
47	ZAF (South Africa)	0.0945	0.0945	0.1527	0.0944	0.0879
48	ZMB (Zambia)	37.014	37.0142	199.8724	37.0795	35.3833
49	ZWE (Zimbabwe)	0.0081	0.0081	0.0455	0.0082	0.0081

heteroscedasticity and non-normality, GLS and Robust standard error is used to correct the problem of heteroscedasticity, Quantile is used for non-normality while Box Cox is used for both heteroscedasticity and non-normality.

Table 5 shows the results for BH7 (Transport), since there exist a problem of heteroscedasticity and non-normality, GLS and Robust standard error is used to correct the problem of heteroscedasticity, Quantile is used for non-normality while Box Cox is used for both heteroscedasticity and non-normality.

The variation in PPP estimates across different regression estimators, as presented in Tables 1–5, highlights the significant impact of methodological choice on the final results. Notably, the Box-Cox transformation consistently yields higher PPP estimates compared to OLS, GLS, robust, and quantile regressions. This inflation can be attributed to the nonlinear nature of the Box-Cox transformation,

Table 4. Estimate of PPP for different estimators under BH5 using Nigeria as ref. country.

S/NO	Country	OLS	GLS	Box Cox	Robust	Quantile
1	AGO (Angola)	1.263	1.2539	1.2933	1.2191	1.2651
2	BDI (Burundi)	10.0245	10.0412	19.4698	10.0898	10.4247
3	BEN (Benin)	3.9454	3.9457	4.9115	3.9653	3.6912
4	BFA (Burkina Faso)	3.5113	3.5119	4.23	3.5396	3.6547
5	BWA (Botswana)	0.0762	0.0762	0.1345	0.0789	0.0778
6	CAF (Central Africa Republic)	5.487	5.4902	7.7404	5.3742	5.4687
7	CIV (Côte d'Ivoire)	3.8338	3.8291	4.6938	3.8338	3.8718
8	CMR (Cameroon)	4.746	4.7425	6.2698	4.7427	4.7272
9	COD (Congo, Dem. Rep.)	8.065	8.0686	13.6854	8.16	7.7671
10	COG (Congo)	4.8633	4.8658	6.543	5.0113	5.3122
11	COM (Comoros)	4.8768	4.8807	6.598	4.9805	4.8876
12	CPV (Cabo Verde)	0.7318	0.7258	0.755	0.7645	0.7744
13	DJI (Djibouti)	1.508	1.5174	1.5846	1.5141	1.5857
14	DZA (Algeria)	0.5676	0.5688	0.5832	0.5702	0.5681
15	EGY (Egypt)	0.0372	0.0372	0.0905	0.0382	0.0377
16	ETH (Ethiopia)	0.0983	0.0981	0.1576	0.1075	0.1036
17	GAB (Gabon)	6.0699	6.0684	8.8621	6.0699	5.8204
18	GHA (Ghana)	0.0118	0.0118	0.053	0.0119	0.0117
19	GIN (Guinea)	37.5861	37.5693	209.5571	37.9607	36.6419
20	GMB (Gambia)	0.1792	0.1794	0.2375	0.1756	0.1605
21	GNB (Guinea-Bissau)	4.8444	4.8465	6.4541	4.8722	4.9188
22	GNQ (Equatorial Guinea)	6.4302	6.4207	9.6692	6.4901	6.3817
23	KEN (Kenya)	0.6121	0.6105	0.6359	0.6087	0.5942
24	LBR (Liberia)	0.009	0.009	0.0475	0.0091	0.0089
25	LSO (Lesotho)	0.065	0.0651	0.1212	0.0662	0.0735
26	MAR (Morocco)	0.0657	0.0657	0.1234	0.0617	0.0571
27	MDG (Madagascar)	11.0272	11.0357	22.7105	11.4567	11.5291
28	MLI (Mali)	4.0639	4.0673	5.162	4.3278	4.4581
29	MOZ (Mozambique)	0.3113	0.3119	0.3609	0.2967	0.2631
30	MRT (Mauritania)	1.8047	1.8041	1.8877	1.7859	1.7438
31	MUS (Mauritius)	0.2752	0.2755	0.3237	0.2628	0.2684
32	MWI (Malawi)	1.4292	1.429	1.4585	1.3681	1.316
33	NAM (Namibia)	0.0635	0.0635	0.121	0.063	0.0652
34	NER (Niger)	3.0923	3.0917	3.6001	3.1143	3.0247
35	RWA (Rwanda)	4.7949	4.8104	6.7045	5.0146	4.9719
36	SDN (Sudan)	0.0203	0.0203	0.0669	0.0208	0.0202
37	SEN (Senegal)	3.8559	3.8487	4.7684	3.7877	3.6236
38	SLE (Sierra Leone)	29.2556	29.2613	128.7011	29.4233	31.9994
39	STP (São Tomé and Principe)	185.2939	185.2122	10147.32	185.2939	182.8294
40	SWZ (Eswatini)	0.0629	0.0629	0.1154	0.0633	0.0636
41	SYC (Seychelles)	0.1253	0.1254	0.1819	0.1255	0.1149
42	TCD (Chad)	4.9819	4.984	6.7187	5.0104	4.8837
43	TGO (Togo)	3.65	3.6499	4.4656	3.8048	3.8231
44	TUN (Tunisia)	0.0132	0.0132	0.0556	0.0125	0.0111
45	TZA (Tanzania)	8.2421	8.2505	14.4412	9.3659	9.7314
46	UGA (Uganda)	19.2651	19.2723	60.1889	20.3573	20.3598
47	ZAF (South Africa)	0.0961	0.096	0.1553	0.1002	0.1045
48	ZMB (Zambia)	43.3155	43.2734	276.33	43.2545	40.2913
49	ZWE (Zimbabwe)	0.0128	0.0128	0.055	0.0126	0.0133

which aggressively adjusts for non-normality and heteroskedasticity in the data. When applied to skewed or outlier-prone price data, the transformation can amplify extreme values, particularly when the estimated transformation parameter (λ) deviates significantly from 1.

To evaluate estimation performance, residual standard errors and standard errors of parameter estimates were computed across BH1, BH2, BH3, BH5, and BH7 for all five models.

Table 6 presents the residual standard errors (RSEs) associated with four estimation methods Ordinary Least Squares (OLS), Generalized Least Squares (GLS), Box-Cox transformation, and Robust regression applied to five basic headings (BH1, BH2, BH3, BH5, and BH7) within the framework of Purchasing Power Parity (PPP) estimation. The residual standard error quantifies the average magnitude of deviations between observed log prices and those predicted by each model, serving

Table 5. Estimate of PPP for different estimators under BH7 using Nigeria as ref. country.

S/NO	Country	OLS	GLS	BOX COX	Robust	Quantile
1	AGO (Angola)	1.1368	1.1204	1.1887	1.1639	1.0864
2	BDI (Burundi)	12.5098	12.3322	29.0415	11.5085	12.0085
3	BEN (Benin)	2.6979	2.6684	3.1242	2.5959	2.7518
4	BFA (Burkina Faso)	3.6023	3.5698	4.4025	3.4546	3.3356
5	BWA (Botswana)	0.0558	0.0552	0.1164	0.0535	0.0554
6	CAF (Central Africa Republic)	4.3978	4.3462	5.8386	4.199	4.1744
7	CIV (Côte d'Ivoire)	4.6493	4.6105	6.1643	4.4716	4.4682
8	CMR (Cameroon)	4.1285	4.0935	5.239	3.9687	4.1897
9	COD (Congo, Dem. Rep.)	9.9652	9.8801	19.0232	9.1725	8.8495
10	COG (Congo)	5.2817	5.2447	7.2984	5.1585	5.0254
11	COM (Comoros)	3.7041	3.6662	4.4828	3.5408	3.3417
12	CPV (Cabo Verde)	0.7796	0.778	0.8012	0.7485	0.7856
13	DJI (Djibouti)	1.8284	1.7947	1.9165	1.766	1.6297
14	DZA (Algeria)	0.4949	0.4938	0.5365	0.4881	0.4952
15	EGY (Egypt)	0.0307	0.0304	0.0833	0.0272	0.0252
16	ETH (Ethiopia)	0.1006	0.0998	0.1617	0.0952	0.1094
17	GAB (Gabon)	6.0973	6.0294	9.2816	5.4108	5.8267
18	GHA (Ghana)	0.0103	0.0102	0.0502	0.0099	0.0098
19	GIN (Guinea)	46.9499	46.5427	345.6828	44.7711	38.4306
20	GMB (Gambia)	0.135	0.1337	0.1984	0.1307	0.1362
21	GNB (Guinea-Bissau)	4.992	4.9295	7.0023	4.8002	5.0282
22	GNQ (Equatorial Guinea)	4.5699	4.5327	6.1502	4.26	3.7535
23	KEN (Kenya)	0.6307	0.6285	0.6619	0.6055	0.694
24	LBR (Liberia)	0.0071	0.007	0.0436	0.007	0.0064
25	LSO (Lesotho)	0.0775	0.0765	0.1341	0.0699	0.0598
26	MAR (Morocco)	0.0753	0.0746	0.1347	0.0722	0.0631
27	MDG (Madagascar)	14.4486	14.2961	35.2411	13.7674	15.0593
28	MLI (Mali)	4.691	4.6518	6.1864	4.4698	4.5558
29	MOZ (Mozambique)	0.3435	0.3406	0.3942	0.3544	0.3617
30	MRT (Mauritania)	1.6466	1.6285	1.7371	1.6237	1.639
31	MUS (Mauritius)	0.303	0.2981	0.3508	0.2759	0.2602
32	MWI (Malawi)	1.559	1.5411	1.6306	1.5058	1.5154
33	NAM (Namibia)	0.0908	0.0895	0.1508	0.0853	0.0807
34	NER (Niger)	3.2634	3.2343	3.9185	3.5326	3.4574
35	RWA (Rwanda)	5.9835	5.8858	9.3461	5.3177	5.1308
36	SDN (Sudan)	0.023	0.0228	0.0715	0.0219	0.0218
37	SEN (Senegal)	4.6522	4.5797	6.4525	4.2519	3.8168
38	SLE (Sierra Leone)	35.0853	34.7811	185.2085	32.5881	29.6336
39	STP (São Tomé and Principe)	167.8634	166.2157	14014.32	158.9193	143.321
40	SWZ (Eswatini)	0.0595	0.0588	0.1135	0.0605	0.063
41	SYC (Seychelles)	0.1224	0.1213	0.1905	0.1215	0.1328
42	TCD (Chad)	4.3215	4.2812	5.5712	4.1443	3.8192
43	TGO (Togo)	4.6241	4.579	6.1731	4.4393	4.9323
44	TUN (Tunisia)	0.0127	0.0126	0.0552	0.0112	0.011
45	TZA (Tanzania)	9.7142	9.6118	18.5118	9.6947	10.4092
46	UGA (Uganda)	16.6648	16.4654	46.3429	15.9986	17.9483
47	ZAF (South Africa)	0.0732	0.0724	0.1331	0.0695	0.0657
48	ZMB (Zambia)	47.747	47.1295	341.2219	47.1406	53.8789
49	ZWE (Zimbabwe)	0.0089	0.0088	0.0475	0.0085	0.0089

Table 6. The Residual Standard Error for the 5 basic headings.

Methods	Residual Standard Error				
	BH1	BH2	BH3	BH5	BH7
OLS	0.263178	0.329225	0.232737	0.34357	0.371576
GLS	**0.255975**	**0.286246**	**0.205961**	**0.325609**	**0.344865**
BoxCox	0.319487	0.368052	0.251194	0.407686	0.461425
Robust	0.257221	0.293806	0.209084	0.328315	0.348045

RSE with the minimum value is bolded.

as a key indicator of model fit. Lower RSE values correspond to greater predictive accuracy and improved reliability of PPP estimates.

Across all basic headings, both GLS and Robust regression consistently yield the lowest RSEs, suggesting superior model performance compared to OLS and Box-Cox transformations. The improved performance of GLS can be attributed to its ability to accommodate heteroscedasticity error structures, which are commonly observed in cross-country price data. Robust regression similarly enhances model fit by mitigating the influence of outliers, a frequent occurrence in internationally sourced datasets. The Box-Cox method performs worst in all cases, delivering the highest RSEs and thus failing to enhance model fit.

Notably, Basic Heading 3 (BH3) records the lowest RSEs under all estimation techniques, implying that the data associated with this category are particularly well-behaved and conducive to accurate modeling. Conversely, Basic Heading 7 (BH7) exhibits the highest RSEs, reflecting increased variability and potential estimation challenges. The relative gains from using GLS over OLS are especially pronounced in BH2 and BH7, where GLS achieves more than a 10 % reduction in residual error compared to OLS, underscoring its robustness in the face of heterogeneity across price observations.

Table 7 reports the standard errors associated with five estimation methods: OLS, GLS, Box-Cox transformation, Robust regression, and Quantile regression applied to five basic headings (BH1, BH2, BH3, BH5, and BH7) under the CPD framework. The standard error quantifies the precision of the estimated coefficients; lower values indicate more reliable and stable parameter estimates. As such, a comparison of standard errors across methods provides insight into the relative efficiency of each estimator.

The results demonstrate that Quantile regression produces the lowest standard errors across all basic headings, suggesting it offers the most statistically efficient estimates in this context. This finding aligns with the robustness of quantile methods in handling non-normal error distributions and heterogeneous variance, which are common characteristics in cross-country price data.

Robust regression also performs well, yielding comparatively low standard errors that are slightly higher than those from Quantile regression but generally lower than those from OLS and GLS.

OLS and GLS show similar standard error magnitudes across all basic headings, with GLS occasionally outperforming OLS marginally. However, neither method consistently improves upon the standard errors observed under Robust or Quantile regression. This suggests that while both OLS and GLS remain valid under ideal assumptions, they may be less suited to the more complex error structures that typify international price data.

In sharp contrast, the Box-Cox transformation results in dramatically inflated standard errors across all basic headings, with values exceeding 60 in BH1 and reaching over 285 in BH7. These extremely high standard errors indicate substantial instability in the coefficient estimates, rendering the Box-Cox method unreliable in this context.

These findings highlight the importance of method selection in international price comparisons, especially for regions like Africa where data quality and economic variability are significant concerns.

Table 7. The Standard Error for the 5 basic headings.

Methods	Standard Error				
	BH1	BH2	BH3	BH5	BH7
OLS	2.617999	3.098831	3.351756	3.896405	3.635341
GLS	2.61168	3.18476	3.35178	3.894647	3.599315
BoxCox	66.22051	102.5117	137.6574	206.8563	285.7126
Robust	2.597674	3.217461	3.335457	3.898779	3.449829
Quantile	**2.530151**	**2.921834**	**3.20967**	**3.843094**	**3.168548**

SE with the minimum value is bolded.

4. Conclusion

This study has examined the application of five estimation techniques for PPP computation in Africa, using the CPD framework with Nigeria as the base country. GLS and Quantile regression emerged as the most reliable methods, offering low residual and standard errors in achieving stable PPP estimates. This finding fully demonstrates that GLS is the best when focusing on model fit while Quantile work better on estimate precision. Due to poor performance of Box-Cox when compared to Quantile regression, researchers are recommended to look into more robust estimators that can give a better estimate precision when handling the problem of heteroscedasticity and non-normality problem simultaneously, likewise heteroscedasticity, non-normality, and autocorrelation simultaneously.

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Conflict of Interest

Authors declare no conflict of interest.

Ethical Approval

This research was conducted in compliance with all applicable ethical standards. The study involved numerical calculations and did not involve any human subjects, animals, or hazardous materials.

Data Availability

No other dataset to declare.

Author Contributions

All authors contributed equally to the manuscript.

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