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Development of a Composite Economic Conditions Index and Multivariate Classification of African Countries Using Minimum Wage, Fuel Price and Exchange Rate Indicators

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ABSTRACT

Minimum wages, fuel prices and exchange rates are all important factors in the cost of living and the macroeconomic environment of households, but are rarely looked at together in one measure. This study constructs a Composite Economic Conditions Index (ECI) for 37 countries in Africa and examines if the economic profiles of these countries are similar to the traditional regional classification of Africa. The indicators were normalised using the min–max method under benefit (minimum wage) and cost (fuel price, exchange rate) criteria and fuel affordability (litres of fuel a monthly minimum wage can purchase) was used as a supplementary indicator. The weights of the index were provided by principal component analysis (PCA), countries with similar profiles were grouped by Ward's hierarchical clustering, and linear discriminant analysis (LDA) was used to determine the ability of region to predict the economic profile. The first three components accounted for 42.48%, 35.52% and 21.99% of the variance, respectively, which suggests low common structure among the indicators. The highest ECI scores were recorded by Eswatini (100.00), Libya (85.97) and Algeria (85.75) while Sierra Leone (0.00) had the lowest score; Nigeria had a score of 69.92 in 18th position. The mean (81.28) for North Africa was the most favourable, while East Africa (61.40) and West Africa (61.82) were the least favourable, with high dispersion within the regions in West and Southern Africa. Ward's method proposed a four-cluster solution and LDA correctly classified only 54.1% of the countries by region (43.2% und er leave-one-out cross-validation). Regional membership is therefore a weak proxy for a country's wage–fuel–currency profile and policy benchmarking is more appropriately based on peer groups based on economic profile.

Keywords: *Composite index; Principal component analysis; Ward's clustering; Linear discriminant analysis; Minimum wage; Fuel price; Exchange rate; Africa.*

1. Introduction

The economy is felt by households in three prices: the price of their earnings, the price of essential energy, and the price of their money in the international market. The statutory minimum wage establishes a lower limit on formal labour earnings, the retail price of fuel directly influences transport costs, and the exchange rate affects the external value of the currency and the domestic cost of imports. These three variables vary greatly across countries in Africa due to different wage-setting institutions, fuel-pricing policies and exchange-rate policies, and because several African countries are oil exporters, subsidising domestic fuel prices, while others are oil importers, charging world prices for fuel [1] [2] It is important for policymakers, regional economic communities and development partners to have a convenient tool to compare such multidimensional conditions between countries. Looking at each indicator individually can result in different rankings: a country with a high minimum wage could also have high fuel prices and a weak currency. A composite index (CI) is a simple way of summarising and providing a convenient basis for ranking and benchmarking, as it is a combination of several normalised indicators [3].

The composite indicator has become a common instrument to summarise complex phenomena, such as human development [4], or competitiveness and well-being. The handbook developed by OECD/JRC outlines the construction process as a series of decisions regarding indicator selection, indicator normalisation, weighting and indicator aggregation and emphasises that each of these decisions should be documented as it influences the final ranking [3]. Concerns are echoed in the field reviews. [5] analysed composite indices of development and found that the rankings could be sensitive to the weights used for the components; [6] criticised the use of composite indicators of country performance without any critical analysis of the weights used; [7] compared different aggregation methods and their compensability properties; and [8] reviewed issues related to weights, aggregation and robustness. [9]

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suggested uncertainty and sensitivity analysis as a method to evaluate the quality of composite indicators. These studies warrant a careful, data-driven and well-documented construction.

1.1 Principal Component Analysis

As a weighting device, the Principal component analysis (PCA) was developed by [10] and elaborated by [11] and is used to transform correlated indicators into uncorrelated components in order of decreasing variance explained; [12] gave an overview of recent developments of PCA. PCA is used extensively to build indices since the weights are derived from the correlation structure of the data and not from subjective judgement. When expenditure data was not available, [13] used the first principal component to create an asset-based wealth index and [14] offered practical advice on how to construct socio-economic status indices using PCA. In macroeconomics, [15] constructed indices of coincident and leading economic indicators based on a set of indicators, and [15] demonstrated that principal components derived from a large set of indicators are useful for forecasting. One of the caveats is that the first component is a meaningful composite only if the indicators are reasonably correlated; if not, the variance is distributed across several components and the single score is a weaker summary.

1.3 Minimum Wage, Fuel Price and Exchange Rate Indicators

There is a vast body of economic research on the minimum wage, and the majority of this research focuses on the employment effects of the minimum wage [16][17]. The level and adequacy of minimum wages vary widely across countries, as do the coverage and compliance of minimum wages, as documented by [18], and the statutory minimum wage is not a perfect indicator of what workers actually receive [19].

The literature on fuel pricing has focused primarily on the role of subsidies: [1] and [20] estimate that global fossil-fuel subsidies are still very high; and [2] considered the fiscal cost of subsidies and the lessons from their reform. The pump price is thus a reflection of world oil market and national policy. Regarding the exchange rate, [21] has claimed that the real exchange rate level is important for economic growth, [22] have demonstrated that the actual exchange rate regime of countries is often different from the regime they officially declare, and [23] have described the monetary regime of Africa, including the CFA-franc zone where currencies are pegged to the euro. The three indicators are thus complementary aspects of the economic situation of a country, but no study to the best of our knowledge has integrated them into a single index for the continent.

1.3 Multivariate Classification.

Cluster analysis is an analysis that groups observations together based on similarity. [24] method combines, at each iteration, the two clusters with the lowest increase in within-cluster variance; [25] explain which algorithms are correctly applying Ward's criterion. [26][27] and [28] provide textbook treatments of cluster analysis and of multivariate methods. If the groups are known beforehand, discriminant analysis, which was developed by [29], separates the variables using linear combinations of the variables, and [30] describe the properties of discriminant analysis and its connection to other classifiers. Cross-validation is the preferred method for estimating misclassification rates, since resubstitution is optimistic [31].

The unsupervised clustering together with the supervised discrimination enables two questions to be asked on the same data: what are the countries that are similar in economic profile, and does a pre-defined grouping (e.g. geographic region) capture those similarities?

2. Methodology

2.1 Source of Data

The study employed cross sectional data of 37 African countries grouped into five regions namely North Africa (6 countries), West Africa (13 countries), Central Africa (3 countries), East Africa (3 countries) and Southern Africa (12 countries). The three main indicators were the statutory minimum wage in US dollars (MW), the retail fuel price in US dollars per litre (FP), and the exchange rate (EXR) in local currency units per US dollar. The fourth indicator, fuel affordability (FA), was calculated as the number of litres of fuel that a month's minimum wage will purchase:

$$FA_i = \frac{MW_i}{FP_i} \quad (1)$$

The Minimum Wage was extracted from International Labour Oganisation (ILOSTAT, 2025) (https://ilostat.ilo.org), Fuel Price from World Bank's World Development Indicators (US$ per litre) (https://databank.worldbank.org) and Exchange rate from International Monetary Fund, International Financial Statistics (https://data.imf.org).

2.2 Normalisation

The indicators were rescaled using the min–max method, taking into account the direction of each indicator [3]. A benefit criterion, under which a higher value indicates more favourable conditions, was applied to minimum wage and fuel affordability:

$$z_{ij} = \frac{x_{ij} - min\ x_j}{max\ x_j - min\ x_j} \quad (2)$$

A cost criterion (with higher values representing less favourable conditions) was used for fuel price and exchange rate (a higher number of local currency units per dollar represents a weaker currency):

$$z_{ij} = \frac{max\ x_j - x_{ij}}{max\ x_j - min\ x_j} \quad (3)$$

Here *xij* is the value of indicator *j* for country *I.*

2.3 Suitability for Principal Component Analysis

The correlation matrix of the normalised indicators was explored and [32] test of sphericity was performed to test the null hypothesis that the correlation matrix is an identity matrix:

$$\chi^2 = -\left[(n - 1) - \frac{2p + 5}{6}\right] ln|R|, df = \frac{p(p - 1)}{2} \quad (4)$$

where n is the number of countries, p the number of indicators and $|R|$ the determinant of the correlation matrix. When only three indicators are analysed, sampling-adequacy measures like Kaiser–Meyer–Olkin statistic [33][34] are not very useful, and therefore, the correlation structure was used to assess suitability. The second step was to use Principal component analysis to construct the index. A correlation matrix of the three normalised primary indicators (MW, FP and EXR) was used for PCA. Fuel affordability was not included in the extraction, but was treated as a supplementary indicator as it is an arithmetically derived indicator from minimum wage and fuel price (Equation 1) and would count the same information twice.

The eigenvalue λ_k and the eigenvector v_k are related by the following conditions:

$$R\, v_k = \lambda_k\, v_k, a_{jk} = v_{jk}\sqrt{\lambda_k} \quad (5)$$

The proportion of variance explained is λ_k/p and components with eigenvalues > 1 were retained, based on Kaiser's [35] criterion. The component score of country k is

$$PCS_{ik} = \sum_j v_{jk}\, s_{ij} \quad (6)$$

with s_{ij} the standardised normalised indicator. The eigenvalue-weighted average of the scores of the retained components was used to obtain the Composite Economic Conditions Index, which was then scaled to range from 0 to 100, with 100 representing the most favourable and 0 the least favourable conditions in the sample:

$$ECI_i = \frac{\sum_k \lambda_k\, PCS_{ik}}{\sum_k \lambda_l}, ECI_i = 100\frac{ECI_i - min\ ECI}{max\ ECI - min\ ECI} \quad (7)$$

The means and standard deviations of the ECI were calculated regionally, and the five regions were compared.

2.4 Hierarchical Cluster Analysis

The standardised (z-score) values of minimum wage, fuel price and exchange rate were clustered by Ward's [24] minimum-variance method with squared Euclidean distance. At each step, the two clusters A and B for which the sum of the squares within the clusters is smallest when they are combined are united:

$$\Delta(A,B) = \frac{n_A n_B}{n_A + n_B}\|c_A - c_B\|^2 \quad (8)$$

where n_A and n_B are the sizes of the clusters and c_A and c_B are the centroids of the clusters. The number of clusters was chosen from the dendrogram by locating large jumps in the merge height.

2.5 Linear Discriminant Analysis

The three indicators were used to predict the region of each country using linear discriminant analysis [29]. The country with indicator vector x is classified to the region with the maximum discriminant function, under the assumption of multivariate normality and a common covariance matrix Σ.

$$\delta_k(x) = x'^{\Sigma^{-1}\mu_k} - \tfrac{1}{2}\,\mu_k'\Sigma^{-1}\mu_k + ln\,\pi_k \quad (9)$$

Here μ_k is the mean vector and π_k the prior probability of region k.

Resubstitution and leave-one-out cross-validation [31] were used to report classification accuracy. The accuracy was compared to the maximum chance criterion (the proportion of the largest group) and to the proportional chance criterion.

$$C_{pro} = \sum_h p_k^2 \quad (10)$$

where *pk* is the proportion of countries in region *k,* and Press's Q statistic,

$$Q = \frac{[N - nK]^2}{N(K-1)},$$

was computed, where N is the sample size, n the number of correct cross-validated classifications and K the number of groups; Q is compared with the chi-square distribution with one degree of freedom [36].

3. Results and Discussion

3.1 Descriptive Statistics

The raw indicators are summarised in Table 1, which is a descriptive statistic. All four have a significant amount of dispersion and a strong right skewness. The minimum wage varies from a nominal US$1 per month in Sudan (where the minimum wage, at the current exchange rate, is virtually insignificant) to US$690 in Eswatini. The prices of fuel vary from US$0.02 per litre in Libya, where fuel is heavily subsidised, to US$3.24 in Malawi. The exchange rates vary from 2.94 local currency units per dollar (Tunisia) to 24,908.74 (Sierra Leone) and fuel affordability ranges from 1.43 litres per month (Sudan) to 2,916.67 litres (Libya). The most skewed variables are the exchange rate (4.88) and fuel affordability (5.63), with a number of extreme countries (Sierra Leone, Libya and Eswatini) dominating their ranges. Raw values are therefore not appropriate for direct aggregation, and this is why the benefit and cost criteria (Equations 2 and 3) allow for the use of min–max normalisation. The normalised indicators are presented in Figure 1, where Libya is at the top for fuel price and fuel affordability, and Eswatini is at the bottom for minimum wage and Sudan and Malawi are near the bottom for minimum wage and fuel price respectively.

Table 1: Descriptive Statistics of the Raw Indicators for 37 African Countries

Variable	Mean	SD	Min	Median	Max	Skewness	Kurtosis
Minimum wage (US$/month)	122.57	125.88	1.00	87.00	690.00	2.90	10.93
Fuel price (US$/litre)	1.37	0.57	0.02	1.47	3.24	0.22	2.85
Exchange rate (LC/US$)	1,504.62	4,296.64	2.94	462.88	24,908.74	4.88	25.92
Fuel affordability (litres)	180.31	474.30	1.43	70.12	2,916.67	5.63	33.39

LC = local currency units. Source: Authors' computation

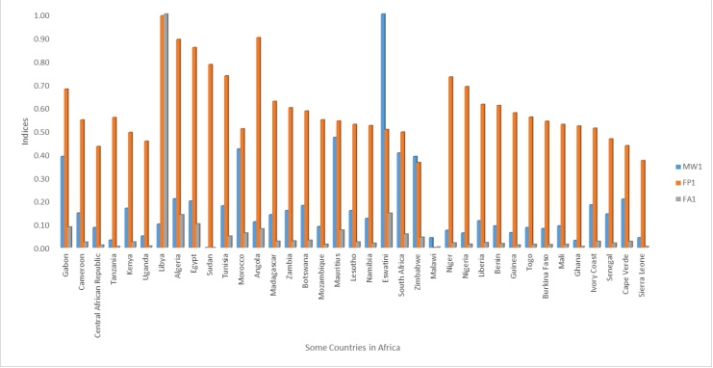


Figure 1. Normalised minimum wage (MW1), fuel price (FP1) and fuel affordability (FA1) for the 37 African countries

3.2 Principal Component Analysis

The correlation matrix of the normalised indicators is shown in Table 2. The pairwise correlations between the three main indicators are low (between −0.066 and 0.217). The only noticeable correlation is between fuel price and fuel affordability, which is partly mechanical, as affordability is calculated as wage/fuel price (Equation 1), so a low fuel price will increase affordability by construction. This helps to make affordability a secondary indicator and not include it with minimum wage and fuel price in the main index.

The identity hypothesis was not accepted for the four indicators ($\chi^2_{(6)} = 13.301, p = 0.038$), but was accepted for the three main indicators ($\chi^2_{(3)} = 3.749, p = 0.29$). This is not a prerequisite for the test, but rather reported for transparency as there are only three indicators and 37 observations, which results in a limited test power [11][14]. It does, however, caution that one dimension will only capture the data to a certain extent.

Table 2: Correlation Matrix of the Normalised Indicators (n = 37)

Indicator	MW	FP	EXR	FA
Minimum wage (MW)	1.000	−0.066	0.215	0.098
Fuel price (FP)	−0.066	1.000	0.217	0.479
Exchange rate (EXR)	0.215	0.217	1.000	0.109
Fuel affordability (FA)	0.098	0.479	0.109	1.000

Bartlett's test: four indicators $\chi^2_{(6)} = 13.301, p = 0.038$; *three primary indicators* $\chi^2_{(3)} = 3.749, p = 0.29$.

Source: *Authors' computation.*

Table 3 gives the PCA results. The three components explained 42.48%, 35.52% and 21.99% of the variance. This balanced distribution is consistent with the weak correlations and with Bartlett's test, and suggests that the indicators are distributed along at least two dimensions that are substantively different. Two eigenvalues are greater than one (1.275 and 1.066), so two components (together explaining 78.00% of the variance) were retained according to the Kaiser (1960) criterion. The first component is positively associated with all three indicators, with the highest association with exchange rate (0.840), followed by fuel price (0.538) and minimum wage (0.529). This was interpreted as a general composite-economic-conditions dimension with the heavy loading on exchange rate indicating that the main source of separation between countries along this dimension is the strength of the currency, with the loading on wage and fuel conditions reinforcing this. The second component compares minimum wage (0.734) with fuel price (−0.726), which means that high wage countries with high fuel prices are compared with low wage countries with low fuel prices, often subsidised; the third component compares the exchange rate (−0.543) with wage and fuel price. These patterns are consistent with the policy-driven price differences reported by [1][20], and support the general argument of [5] and [8] that a single component cannot be used to represent all the information.

Table 3: Principal component loadings and variance explained

Indicator	PC1	PC2	PC3
Minimum wage	0.529	0.734	0.426
Fuel price	0.538	−0.726	0.429
Exchange rate	0.840	0.002	−0.543
Eigenvalue	1.275	1.066	0.660
Variance explained (%)	42.48	35.52	21.99
Cumulative variance (%)	42.48	78.00	100.00

Source: *Authors' computation.*

3.3 Composite Economic Conditions Index by Country.

The ECI for each country was calculated by applying the weights (eigenvectors) of the retained components (1.275 and 1.066) and is displayed in Figure 2. Eswatini has the highest minimum wage in the sample, and is ranked first (ECI = 100.00), followed by Libya (85.97) with very low fuel prices and Algeria (85.75). Sierra Leone is the lowest with a score of 0.00, which is mainly due to the high exchange rate of its local currency (about 24,909 local currency units per dollar), followed by Malawi (42.07) and Guinea (47.62), which have the highest fuel price in the sample.

Nigeria's ECI of 69.92 is in the middle of the distribution of the countries and ranks 18th, higher than the West African regional mean of 61.82.

Two cautions apply. First, the nominal exchange rate has the highest loading on the first component, so the index is heavily weighted by the nominal exchange rate and the very low score for Sierra Leone is largely responsible for the low end of the index. Second, the minimum wage is converted into dollars using the current exchange rate, which means that the wage and the exchange rate are not independent: if the currency depreciates, the dollar value of the wage will be reduced (US$1 in Sudan is an example). Therefore, the ECI should be interpreted as a description of the cost and income situation of a minimum wage earner in dollars, rather than as an indicator of macroeconomic performance.

3.4 Regional mean Composite Economic Conditions Index

The regional means are shown in Table 4 and Figure 3. North Africa has the best conditions (mean ECI = 81.28) and the least spread within the region (SD = 4.96), followed by Southern Africa (72.76) and Central Africa (71.83). East Africa (61.40) and West Africa (61.82) have the lowest averages. However, the within-region variation is frequently as great as the differences between the regional means (61.40 to 81.28), which cover only 19.88 points. In Southern Africa, the scores range from 42.07 (Malawi) to 100.00 (Eswatini) with a standard deviation of 13.47; in West Africa, Sierra Leone (0.00) is much lower than the other 12 countries, which range up to 73.73, with a standard deviation of 19.60. The mean and standard deviation for regions with three countries (Central and East Africa) are unstable. The regional averages mask significant variation, which is demonstrated by the following cluster analysis. There was no formal test of equality of regional means, and with these small group sizes and outliers, one would need a robust or nonparametric procedure.

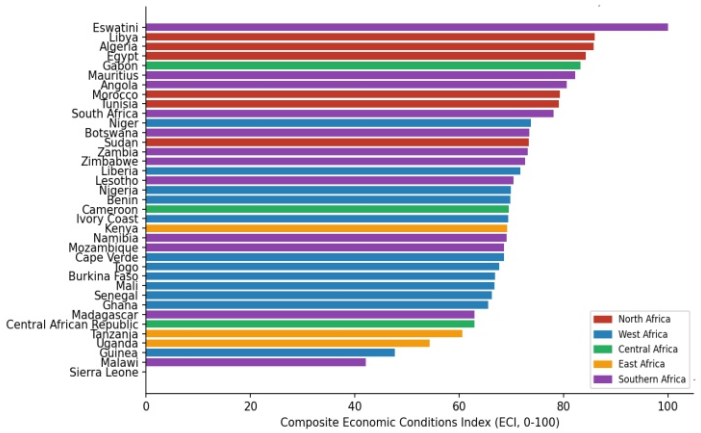


Figure 2. Composite Economic Conditions Index (ECI) by country

Table 4: Mean ECI by region

Region	Countries	Mean ECI	SD	Min	Max
North Africa	6	81.28	4.96	73.35	85.97
West Africa	13	61.82	19.60	0.00	73.73
Central Africa	3	71.83	10.36	62.88	83.19
East Africa	3	61.40	7.46	54.37	69.22
Southern Africa	12	72.76	13.47	42.07	100.00

Source: *Authors' computation.*

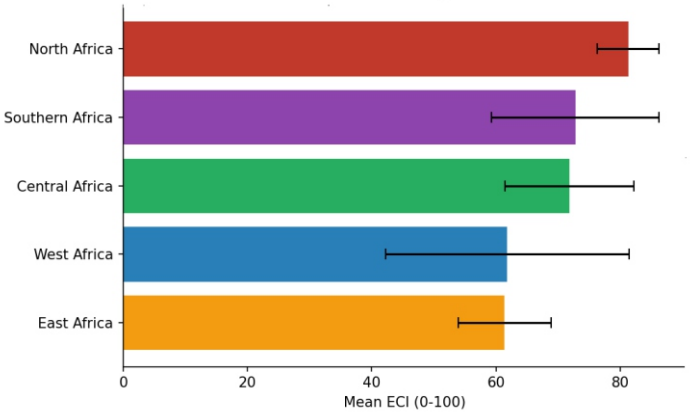


Figure 3. Mean ECI by region with standard deviation error bars

3.5 Hierarchical cluster analysis

The normalised minimum wage, fuel price and exchange rate were used for Ward's method. The dendrogram (Figure 4) indicates that there are significant gaps in merge height at approximately 4.3, 6.2, 7.2 and 8.2, suggesting a four-cluster solution, and the profiles are presented in Table 5. The first cluster (Gabon, Morocco, Mauritius, Eswatini, South Africa and Zimbabwe) has the highest minimum wages (mean US$354.70 per month), typical fuel prices (US$1.57 per litre) and comparatively strong currencies, with the exception of Eswatini, which has US$690.

The second cluster (Libya, Algeria, Egypt, Sudan, Tunisia, Angola, Niger and Nigeria) has very low fuel prices (mean US$0.58 per litre) and low wages (around US$81), which is typical of oil-producing economies and fuel-subsidy regimes [1][2]. The third and largest cluster (22 countries from West, Central, East and Southern Africa) is characterised by low wages (around US$78.50) and mid-range fuel prices (around US$1.58); the many near-zero fusions among its members are due to the shared CFA-franc exchange rate [23], and Malawi, with the highest fuel price in the sample (US$3.24), is its most unusual member. Sierra Leone is a singleton cluster due to its exchange rate being much higher than the rest of the countries.

There are two points that should be stressed. The clusters span across regions: the low cost of fuel cluster includes North African, West African, Central African and East African countries; the high cost of fuel cluster includes North, Central and Southern African countries. Moreover, cluster membership refers to the time period of the data, with countries that reform fuel pricing or exchange-rate arrangements shifting between clusters, consistent with the results of [22] that practised arrangements change over time. The solution is also sensitive to the outliers, as is typical of variance-based hierarchical methods [26][25], due to the very unequal size of the singleton and the largest cluster.

Table 5: Profile of the four-cluster Ward solution

Cluster	n	MW (US$/mo.)	FP (US$/L)	EXR (median)	Countries
1. Higher-wage	6	354.7	1.57	21.5	Gabon, Morocco, Mauritius, Eswatini, South Africa, Zimbabwe
2. Cheap-fuel	8	81.4	0.58	298.9	Libya, Algeria, Egypt, Sudan, Tunisia, Angola, Niger, Nigeria
3. Low-wage, mid fuel-price	22	78.5	1.58	573.0	Remaining 22 countries (including Malawi)
4. Singleton	1	30.0	2.03	24,908.7	Sierra Leone

Values are cluster means, except the exchange rate (median). MW = minimum wage; FP = fuel price; EXR = exchange rate. Source: Authors' computation.

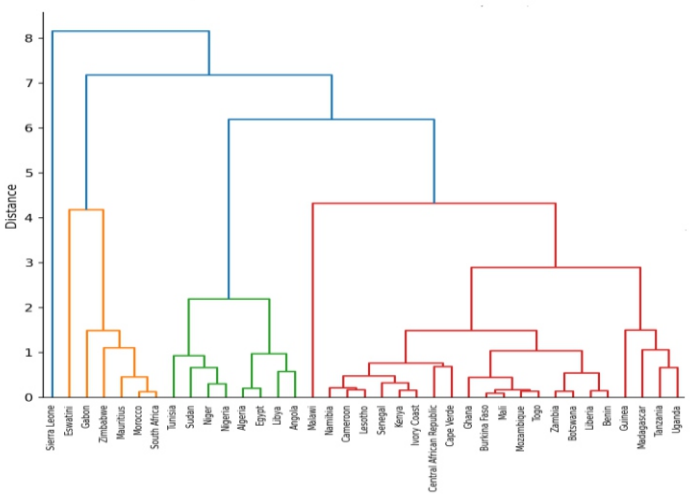


Figure 4. Ward hierarchical clustering dendrogram of the 37 countries on mormalised indicators

3.6 Linear Discriminant Analysis

Table 6 reveals that LDA performed moderately well, with 54.1% (20 of 37 countries) accuracy using resubstitution and 43.2% (16 of 37 countries) using leave-one-out cross validation. There was a reasonable classification of North Africa (4 of 6 countries) and best (11 of 13 countries) in West Africa, but no country was assigned to Central or East Africa, both of which were lumped into the West African and Southern African classifications, and only 5 of 12 Southern African countries were correct, with 6 being allocated to West Africa. The optimism shown in the drop from resubstitution to cross-validated accuracy is the optimism that is expected of a resubstituted estimate [31] and is magnified here by the small sample and by regions having only three members.

Three benchmarks were calculated based on the region sizes (6, 13, 3, 3 and 12 countries), to determine whether the accuracy is better than chance. The maximum-chance criterion is 35.1% (13/37) and the proportional chance criterion is 26.8% [$(6^2 + 13^2 + 3^2 + 3^2 + 12^2)/37^2$]. The cross-validated accuracy of 43.2% is higher than both, and Press's Q = $[37 - (16 \times 5)]^2 / [37 \times 4]$ = 12.49 is higher than the 5% critical value of 3.84 for 1 degree of freedom, indicating that the predictive power is statistically better than chance [36]. The improvement is still limited, however, and the model is largely based on the recognisable West African and North African profiles. The clusters in Section 3.5 are in line with Region being a statistically detectable but weak predictor of a country's joint wage, fuel-price and exchange-rate profile. As LDA assumes normality and equal covariance matrices, which cannot be verified reliably with three observations in some groups, a regularised or nonparametric classifier (Hastie et al., 2009) would be a useful check.

Table 6: LDA confusion matrix (resubstitution)

Actual \ Predicted	North Africa	West Africa	Southern Africa	n	Correct (%)
North Africa	4	1	1	6	66.7
West Africa	0	11	2	13	84.6
Central Africa	0	2	1	3	0.0
East Africa	0	2	1	3	0.0
Southern Africa	1	6	5	12	41.7

Overall accuracy = 54.1% (20/37); leave-one-out cross-validated accuracy = 43.2% (16/37).
***Source:** Authors'*

3.7 Discussion

The results lead to a consistent conclusion. The low correlations between the indicators, the even distribution of variance by component, and the cross-regional nature of the clusters and the relatively low discriminant accuracy demonstrate that minimum wage, fuel price and exchange rate represent different facets of national economic conditions that are not easily mapped to geography. Policy-wise, it means that the benchmarking should be based on peer groups based on economic profile, not regional blocks, as Nigeria is in the cheap-fuel group. For instance, a country in the cheap-fuel cluster has a different trade-off between subsidy reform and the real value of wages than a country in the low-wage, mid-fuel cluster, and the ECI helps to position each country in relation to the others. The results are in line with the literature on composite indicators which suggests that an index is a valuable tool to begin a discussion but should be used in conjunction with its components [3][8].

There are a number of caveats. Analysis is cross-sectional, so cannot demonstrate changes over time. Statutory minimum wages overlook informal employment and non-compliance [18][19]. The nominal exchange rate in local currency per dollar is influenced by the way the currency is denominated and whether the official and parallel market rates differ, and thus reflects more than the strength of the currency; a real effective exchange rate or a log-transformed depreciation measure would be preferable, and the dominance of exchange rate on the first component should be interpreted in that context. The min–max normalisation is sensitive to extreme values and the PCA weights were estimated from weakly correlated indicators. Finally, the results were not exposed to the uncertainty and sensitivity analysis suggested by Saisana et al. (2005), such as comparing PCA weights with equal weights. Panel data could be used in future, inflation indicators added, and robustness of the ranking tested to other normalisation, weighting, and clustering choices, such as k-medoids methods [27].

4. Conclusion

This study created a Composite Economic Conditions Index based on minimum wage, fuel price and exchange rate for 37 African countries and applied it in conjunction with cluster analysis and discriminant analysis to investigate if the region membership reflects economic profile. Only weak correlations between the indicators, the first three principal components accounted for 42.48%, 35.52% and 21.99% of the variance, and two components with eigenvalues greater than one were used to construct the index. The best scores were for Eswatini, Libya and Algeria, while Sierra Leone had the worst score, and Nigeria was ranked 18th (ECI = 69.92).

The regional mean was highest in North Africa (81.28) and lowest in East and West Africa, but there was considerable variation within regions, especially West and Southern Africa. Ward's method yielded four clusters that spanned regions, while LDA correctly classified 54.1% of countries by region (43.2% by cross-validation) which is better than chance, but weak.

The primary finding is that region is not a perfect indicator of the wage, fuel-price and currency environment of a country. Policy comparisons and regional benchmarking are recommended to be done at the economic-profile group level, the ECI is recommended to be reported in conjunction with its component indicators, and future studies are recommended to be based on multi-year data, real exchange-rate measures, and sensitivity analysis of the weighting scheme to enhance the evidence.

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