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An Analysis of Panel Data on Unemployment and Labor Force Participation Rates in Sub-Saharan African Countries

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Abstract
This study investigates the correlation between unemployment rates and rates of participation in the labor force in 46 countries in Sub-Saharan Africa over a span of 32 years, from 1991 to 2023. The data used for this analysis is sourced from an online database. Both the Kao and Pedroni panel cointegration tests produce statistically significant findings, suggesting a robust long-term association between the two variables. The Johansen cointegration test provides further validation for these findings, enhancing their robustness. Granger causality studies indicate that there is a one-way causal relationship from labor force participation rates to unemployment. This suggests that changes in labor force participation have an impact on the levels of unemployment. Using a fixed effect model, we see notable coefficients for both male and female labor force participation rates, indicating their adverse effect on unemployment rates. The analysis highlights the crucial influence of labor force participation on unemployment rates in Sub-Saharan African nations. The study's findings offer significant direction for policymakers and researchers to develop focused interventions aimed at improving labor force participation and addressing unemployment concerns in the region.

Keywords: Unemployment, Labor Force, Panel Cointegration, Panel Regression models

INTRODUCTION
This study investigates the enduring correlation between unemployment and labor force participation rates worldwide during the previous decade. The link between unemployment and labor force participation is an important problem in labor economics and development statistics. The article primarily explores the long-run relationship between unemployment and labor force participation rates across Sub-Saharan African countries, which are predominantly emerging nations. The nature of the relationship between unemployment and labor force participation is an important problem with wide-ranging consequences for macroeconomic theory, applied modeling, and labor market policy. There are other instances that exemplify the importance of this correlation. For instance, labor force participation may change across the business cycle due to the "discouraged worker impact." As a result, the unemployment rate may not properly reveal the underlying level of labor market circumstances. Several authors, such as Murphy & Topel (1997), Gustavson & Österholm (2006), and Ozdemir et al. (2013), have discussed this occurrence. The complicated relationships between unemployment and labor force participation have substantial repercussions for macroeconomic analysis, modeling methodologies, and the creation of successful labor market policy.

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Another notable example is the unemployment invariance theory, which indicates that the long-term unemployment rate is independent of factors like as the labor force, capital stock, and total factor productivity. Researchers like Layard et al. (1991) and Kögel (2005) have supported this hypothesis. However, the unemployment invariance hypothesis has also been criticized, by Karanassou and Snower (2004). The debate around this idea underlines the intricate relationship between unemployment and labor force participation, as well as the significance of further exploring these processes. The unemployment invariance hypothesis is another example of the major consequences the unemployment-labor force participation link has for macroeconomic theory and policy. The diverse perspectives on this concept illustrate the necessity for additional research and analysis in this field.

Another noteworthy feature of the relationship between unemployment and labor force participation is the importance of the unemployment invariance hypothesis. This theory indicates that the long-run unemployment rate is independent of the size of the labor force. The research on this subject has thoroughly analyzed governments' reactions to this issue, as well as the implications of neglecting to involve young people and fulfill their needs. The purpose of this study is to evaluate the long-run link between unemployment and labor force participation rates. The purpose is to give new empirical information to better understand and forecast the breadth and persistence of these occurrences in the sub-Saharan African economy. This research focuses on the dispute around the unemployment invariance hypothesis and the policy implications of the unemployment-labor force participation link. The study intends to contribute to a greater understanding of these complicated macroeconomic dynamics in the context of developing Sub-Saharan African countries.

The link between unemployment and labor force participation is an important problem in the domains of labor economics and development statistics. There have been several research that study the long-run relationship between unemployment and the labor force participation rate, but they have yielded diverse results.

Table 1**:** Overview of Some Selected Studies

Authors	**Period**	**Empirical Method/ Methodology**	**Study Area**	**Variables**	**Finding**
Muhammad, et al. (2020)	1990 – 2017	Johannsen's Co-integration, VEC Model	Nigeria	Labor force participation rate growth fixed capital formation and real gross domestic product.	The study found that unemployment and labor force participation rates have a long-run relationship. Additionally, long-run causality was identified, running from labor force participation rate (LFPR) and gross fixed capital formation (GFCF) to real GDP (RGDP).
Nicholas and Ibrahim (2017)	1967 - 2014	Durbin-hausman co-integration test	US of America	Unemployment and labor force participation	The results of the study indicate the presence of a relationship between unemployment and labor force participation.
Saridakis, *et al.* (2016)	1990 - 2011	Panel co-integration approach's	European OECD Countries	Self-employment and unemployment.	Their findings indicated that long-run relationship between unemployment and self-employment exist in the panel, but co-integrating coefficients are unstable.

Nemore, *et al.* (2021)	1988-1991	Johansen methodology Dicky Fuller test	Italy	Unemployment and labor force participation rate.	The co-integration analysis results strongly suggest there is a clear long-run relationship between unemployment and labor force participation. This finding reveals the presence of a persistent and general "added worker effect".
Angel, and Angel, 2023)	2006-2019	Vector error correction model (VECM)	Six countries in Latin America (Ecuador, Chile, Peru, Uruguay, Brazil & Mexico)	Labor force participation and unemployment rate.	No long-run equilibrium relationship between unemployment and labor force participation for the aggregate models of Brazil and Mexico. However, such a long-run equilibrium relationship was evident for the economies of Ecuador, Chile, Peru, and Uruguay.

MATERIALS AND METHODS
The section introduces and briefly described the data and technique applied in the study

Data
Annual data extending from 1991 to 2022 covering 46 Sub-Saharan African countries will be utilized. The data were taken from the theglobaleconomy.com an internet database.

Table 2: Description of Variables

Variables	Description	Source
UNER	Unemployment rate	theglobaleconomy.com
MLFR	Male Labor Force participation rate	theglobaleconomy.com
FLFR	Female Labor Force Participation rate	theglobaleconomy.com

Methodology
This section offers the panel unit tests, panel cointegration tests, the causality test among the variables and panel regression models for testing the link that exist between the variables of interest.

Panel Unit Root Tests
The paper notes that there are numerous ways available in the literature to determine the presence of unit roots in panel data. The specific tests considered in this research include the Breitung (2000) test, the Levin, *et al*. (2002) (LLC) test, the Im, *et al.* (2003) [W-test (IPS)], the ADF-Fisher Chi-square test (ADF-Fisher), the PP Fisher Chi-Square test (PP-Fisher), the Maddala and Wu (1999) test, and the Hadri (2000) test. For all these unit root tests, the Hadri test, the null hypothesis is that the variable under study includes a unit root.

Panel unit root testing is a vital first step in doing co-integration analysis. This is because co-integration requires the variables to have particular stationarity properties. Many macroeconomic variables tend to exhibit trends, therefore understanding the time-series features of the panel data is vital. The panel unit root tests used in the literature can be generally classified into two primary groups: First-generation tests: These presume the panel data variables are cross-sectionally independent. Examples include experiments by Maddala and Wu (1999), Hadri (2000), Choi (2001), Levin *et al.* (2002), and Im *et al.* (2003). Second-generation tests: These explicitly account for and allow for some form of cross-sectional dependence among the variables. The second-generation tests presume heterogeneity, meaning there is no common autoregressive (AR) structure across the panels. The contrast between these two generations of panel unit root tests is significant, as the first-generation tests can be biased if there are cross-sectional dependencies present in the data. The second-generation experiments try to address this constraint.

Panel Cointegration Tests

The researchers utilized both sorts of co-integration tests: those with a null hypothesis of "no co-integration" and those with a null hypothesis of "co-integration." The core concept behind these residual-based co-integration tests is to check whether the residuals from the co-integrating regression equation include a unit root or not. If the residuals are determined to have a unit root, this means there is no co-integrating relationship between the variables in the model. Conversely, the absence of a unit root in the residuals provides evidence of a co-integrating relationship between the dependent and independent variables. These co-integration tests are premised on the assumption that there is just a single co-integrating relationship present between the variables being evaluated. By utilizing both types of panel co-integration tests, the study hoped to completely analyze the long-run equilibrium relationship between the variables in the model.

Residual-Based Tests

The first residual-based panel co-integration tests were introduced by Pedroni (1995). In later work, Pedroni (1999, 2004) extended this panel co-integration testing approach to the scenario of several regressors. Pedroni (1999, 2004) presented seven distinct residual-based panel co-integration tests to assess the null hypothesis of "no co-integration": Four "within-dimension"-based tests: panel-v statistic, panel-ρ statistic, semi-parametric panel-t statistic, and parametric panel-t statistic. Three "between-dimension"-based tests: group-ρ statistic, semi-parametric group-t statistic, and parametric group-t statistic. The key starting point for these Pedroni panel co-integration tests is the computation of the residuals from the postulated co-integrating regression equation. The within-dimension tests total up the numerator and denominator components independently across the N cross-sections. In contrast, the between-dimension tests first split the numerator and denominator and then total up across the N cross-sections. This comprehensive collection of seven residual-based panel co-integration tests, established by Pedroni, provides a robust methodology to analyze whether the variables in a multiple regression model have a stable, long-run co-integrating relationship.

$$y_{it} = \delta_{\circ i} + \delta_{1it} + x_{it}^{'}\beta_i + \ell_{it} \tag{1}$$

where $i = 1,.....,N$; $t = 1,.....,T$; in which T is the number of observations over time and N denotes the number of individuals in the panel. y_{it} and the K-dimensional vector of independent variables $x_{it} = x_{it-1} + v_{it}$ are assumed to be at most $I(1)$. The co-integrating vector $\beta_i = (\beta_{1i},.....\beta_{ki})^{'}$, the individual specific intercept $\delta_{\circ i}$ and the trend parameter δ_{it} can vary over cross-sections.

Panel Causality Test

After proving the presence of co-integration between the variables, the next step is to assess the direction of causality between them using panel causality tests. The co-integration between the variables means that there must be a causal relationship between them in at least one direction. The researchers continue by employing the two-step Engle & Granger (1987) technique to test for causation. Engle & Granger showed that if two non-stationary variables

are co-integrated, a typical vector autoregression (VAR) model in first differences will be misspecified. Instead, when there is discovered to be a long-run equilibrium (co-integrating) relationship between the variables, the suitable model for assessing Granger causality is an error correction representation. This includes enhancing the standard VAR model with a one-period lagged error correction term, which is produced from the co-integrating model. This error correction representation ensures that the short-run dynamics of the model capture the adjustment towards the long-run equilibrium, in addition to checking for the direction of Granger causality between the variables.
The following error correction form can represent the two cointegrated variables:

$$\Delta uner_{it} = \alpha_{1i} + \sum_{p} \alpha_{11ip} \Delta uner_{it-p} + \sum_{p} \alpha_{12ip} mlfr_{it-p} + \sum_{p} \alpha_{13ip} flfr_{it-p} + \psi_{1i} ECT_{t-1} + \varepsilon_{1it} \quad (2)$$

$$\Delta mlfr_{it} = \alpha_{2i} + \sum_{p} \alpha_{21ip} \Delta mlfr_{it-p} + \sum_{p} \alpha_{22ip} uner_{it-p} + \sum_{p} \alpha_{23ip} flfr_{it-p} + \psi_{2i} ECT_{t-1} + \varepsilon_{2it} \quad (3)$$

$$\Delta flfr_{it} = \alpha_{3i} + \sum_{p} \alpha_{31ip} \Delta flfr_{it-p} + \sum_{p} \alpha_{32ip} uner_{it-p} + \sum_{p} \alpha_{33} mlfr_{it-p} + \psi_{3i} ECT_{t-1} + \varepsilon_{3it} \quad (4)$$

Here Δ denotes the first difference of the variable, ECT is the error-correction term, it derived from the long run co-integrating relationship (this term is not included if the variables are not co-integrated), while ε_{1it}, ε_{2it} and ε_{3it} are serially independent random errors with mean zero and finite covariance matrix, p donates the lag length $(\mathrm{p} = 1, 2, 3)$ and ψ_{pi} is the adjustment speed of error correction term. A significant value for ψ_{pi} implies that the short-run disequilibrium may be adjusted into long-run equilibrium through the ECT process. The ψ_{pi} measures how fast deviations from the long-run equilibrium are eliminated following changes in the unemployment and labor force participation rate.

Panel Regression Models
Panel data models allow for the investigation of individual behavior over both time and individual units. They can account for heterogeneity or individual-specific effects, which may or may not be explicitly observed (Park, 2011). These individual-specific effects and time effects can be described as either fixed effects or random effects in the panel data framework. There are three basic types of panel data models that can be employed in the analysis: pooled models, fixed effects models, and random effects models.

Pooled model
Pooled model defines coefficients, the standard assumptions for cross-section analysis is the most restrictive panel data model, which assumed that there is no heterogeneity i.e the same connection holds for all the data and it has same intercept.

$$y_{it} = \alpha + x_{it}^{'} \beta + u_{it} \quad (5)$$

Fixed effects model

$$y_{it} = \alpha + \beta x_{it} + u_i + v_{it} \quad (6)$$

In this model u_i summarizes all of the variables that affects y_{it} cross-sectionally but do not vary over time, thus it captures the heterogeneity in u_i by allowing for diverse intercepts for each cross-sectional unit, fixed effect model could be estimated using dummy variables; LSDV approach

$$y_{it} = \beta x_{it} + u_1 D1_i + u_2 D2_i + u_3 D3_i + \ldots + u_N DN + v_{it} \quad (7)$$

$D1_i$ a dummy variable (=1 for all observations on the first entity in the sample and zero otherwise). $D2_i$ a dummy variable (=1 for all observations on the second entity and zero otherwise), etc. The LSDV can be seen as just a standard regression model and therefore estimated by OLS the model above has N+k parameters to estimate, to avoid estimating so many dummy variable parameters, a transformation, known as the within transformation, is used in subtracting the time-mean of each entity away from the values of the variable.

Random Effect Model

The Random Effect Model has different intercept terms for each entity and these intercepts are constant over time, the intercepts assumed to evolve from a common intercept α plus a random variable ε_i (varies cross-sectional but is constant over time).

$$y_{it} = \alpha + \beta x_{it} + \omega_{it} \quad (8)$$

$\omega_{it} = \varepsilon_i + v_{it}$ and ε_i measures the random deviation of each entity's intercept term from the "global" intercept term α, in contrast to fixed effect, no dummy variables to capture the heterogeneity(variation) in the cross-Sectional dimension, this occurs via ε_i terms.

RESULTS AND DISCUSSION

This section contains the panel data analysis and discussion of the results.

Panel Unit Root Tests

For cointegration analysis to take place all variables are required to be nonstationary. Numerous panel unit root testing procedures are performed to identify the order of integration of all variables under consideration, we first take panel unit root tests to evaluate their order of integration.

Table 3: Panel Unit Root Tests Results

Tests Assuming Common Unit Root Processes						
Series Names	**LLC t-stat:**		**Breitung t-stat:**		**Hadri z-stat:**	
	Null: Unit Root		**Null: Unit Root**		**Null: Stationary**	
	No Trend	**Trend**	**No Trend**	**Trend**	**No Trend**	**Trend**
UNER	0.8862	0.0095	-	0.7023	0.0000	0.0000
ΔUNER	(0.0000)	(0.0000)	-	(0.0022)	(0.0000)	(0.0000)
MLFR	0.0000	0.1512	-	1.0000	0.0000	0.0000
ΔMLFR	(0.0000)	(0.0000)	-	(1.0000)	(0.0000)	(0.0000)
FLFR	0.0000	0.0088	-	1.0000	0.0000	0.0000
ΔFLFR	(0.0029)	(0.7633)	-	(1.0000)	(0.0000)	(0.0000)

Table 4: Panel Unit Root Tests Results

	Tests Assuming Individual Unit Root Process					
Series Names	ADF Fisher χ^2:		PP Fisher χ^2:		IPS W-t-bar-test:	
	Null: Unit Root		Null: Unit Root		Null: Unit Root	
	No Trend	Trend	No Trend	Trend	No Trend	Trend
UNER	0.8678	0.2320	1.0000	0.9999	0.9989	0.6702
ΔUNER	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MLFR	0.3750	0.5238	0.2541	0.6046	0.8571	0.9058
ΔMLFR	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FLFR	0.3059	0.4879	0.2366	0.7291	0.5426	0.5013
ΔFLFR	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

The study conducted panel unit root tests on variables, revealing non-stationary at level results. Breitung (2000) and Hadri (2000) test statistics showed non-stationary variables, while Levin Lin & Chu test statistic showed mixed results. All tests assumed individual unit root processes, with all showing non-stationary variables. The Hadri test strongly imply unit root at level across variables, confirming the series are integrated of order I(1) and variables have unit roots.

Panel Cointegration Tests

Following the evidence that the series has a unit root, which suggests that a linear combination of these nonstationary variables is likely to produce stationary error terms, we apply three different panel cointegration tests, namely, Pedroni (1999), Kao (1999) and Johansen Fisher Cointegration test statistics. Both tests were employed to discover whether there are long-run correlations amongst the variables, using a null hypothesis of “no cointegration." The result below is the outcome of the Kao Cointegration Test.

Table 5: Kao Panel Cointegration Test Results

Kao(UNER as dependent variable)		
Null: No Cointegration	**t-statistic**	**Probability**
ADF	-2.115999	0.0172

Null Hypothesis: No cointegration
Trend assumption: No deterministic trend
User-specified lag length: 1

Table 5 shows the Kao panel cointegration test, which rejects the null hypothesis of no cointegration between variables of interest, indicating a long-term association between unemployment and labor force participation rates in sub-Saharan African countries. The Pedroni panel cointegration test, devised by Pedroni (2004), confirms this association.

Table 6: Pedroni Panel Cointegration Test Results

Pedroni (UNER as dependent variable)		
Null: No Cointegration	**Test statistic**	**Probability**
Within-Dimension		
Panel-v	1.651926	0.0493
Panel-rho	1.576639	0.9426
Panel-PP	-2.004598	0.0225
Panel-ADF	-4.423621	0.0000
Between-Dimension		
Group-rho	4.074924	1.0000
Group-PP	0.150630	0.5599
Group-ADF	-3.418103	0.0003

Null Hypothesis: No cointegration
Trend assumption: Deterministic intercept and trend
User-specified lag length: 1
Newey-West automatic bandwidth selection and Bartlett kernel

Pedroni panel cointegration test assesses cointegration linkages in variables. It uses four within-dimension and three between-dimension panel statistics tests. The null hypothesis is no cointegration, but alternative hypothesis suggests cointegration. Panel-v, Panel-PP, Panel-ADF, and Group-ADF statistics reject the null hypothesis, suggesting panel cointegration. The Johansen cointegration test uses trace and maximum eigenvalue criteria at a 0.05 significance level.

Table 7: Johansen Fisher Cointegration Test Result

Johansen-Fisher (UNER as dependent variable)				
Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	**Probability**	Fisher Stat.* (from max-eigen test)	**Probability**
None	701.5	0.0000	574.5	0.0000
At most 1	275.4	0.0000	212.7	0.0000
At most 2	224.6	0.0000	224,6	0.0000

* Probabilities are computed using asymptotic Chi-square distribut...

Table 7 shows that the assumption of no cointegration relationship, one cointegration relationship, or two cointegration relationships is rejected, indicating a long-term relationship between unemployment and labor force participation rates in Sub-Saharan African countries.

The study reveals that several African countries, including the Democratic Republic of Congo, Ethiopia, Gabon, Guinea, Madagascar, Mauritius, Niger, and Sao Tome, lack cointegration relations in both trace and maximum eigenvalue tests. However, Burundi, Eritrea, Mauritania, Senegal, and Tanzania show cointegration relations.

Table 8: Estimation Result of the Johansen-Fisher Individual Cross-Sectional Cointegration

Individual cross section results

Cross Section	Trace Test Statistics	Prob.**	Max-Eign Test Statistics	Prob.**
Hypothesis of no cointegration				
Angola	46.8184	0.0002	28.2614	0.0042
Benin	43.2902	0.0008	29.4780	0.0027
Botswana	29.8643	0.0491	22.7033	0.0298
Burkina Faso	48.9501	0.0001	26.6192	0.0076
Burundi	30.4803	0.0417	16.7407	0.1846
Cameroon	36.5613	0.0071	22.8300	0.0286
Cape Verde	175.6138	0.0000	119.1616	0.0000
Central Africa...	42.9882	0.0009	33.9642	0.0005
Chad	127.8898	0.0000	104.0730	0.0000
Comoros	43.4727	0.0008	27.3574	0.0058
Democratic R...	24.0741	0.1973	16.8609	0.1787
Equatorial Gu...	47.5357	0.0002	21.8601	0.0395
Eritrea	41.1802	0.0016	19.0025	0.0968
Ethiopia	29.5505	0.0534	16.5693	0.1933
Gabon	28.7773	0.0652	19.8632	0.0745
Gambia	50.5562	0.0001	39.9590	0.0001
Ghana	36.5999	0.0071	24.2623	0.0175
Guinea	26.6159	0.1114	13.6064	0.3982
Guinea-Bissau	66.2770	0.0000	61.1684	0.0000
Ivory Coast	57.3670	0.0000	47.8895	0.0000
Kenya	46.9474	0.0002	25.1851	0.0127
Lesotho	53.6724	0.0000	39.8028	0.0001
Liberia	48.2340	0.0001	33.4953	0.0006
Madagascar	28.6004	0.0682	13.3380	0.4216
Malawi	46.4558	0.0003	39.0966	0.0001
Mali	50.6272	0.0001	35.3893	0.0003
Mauritania	36.7217	0.0068	16.7862	0.1823
Mauritius	25.1385	0.1565	16.5916	0.1922
Mozambique	58.8909	0.0000	42.2153	0.0000
Namibia	34.8913	0.0119	23.8006	0.0205
Niger	24.7868	0.1692	12.3989	0.5088
Nigeria	42.9295	0.0009	22.7357	0.0295
Republic of th...	60.1032	0.0000	42.1934	0.0000
Rwanda	92.5119	0.0000	80.3309	0.0000
Sao Tome an...	27.5992	0.0878	13.3640	0.4193
Senegal	30.5181	0.0412	20.1243	0.0687
Sierra Leone	38.1325	0.0044	26.0470	0.0094
Somalia	53.7813	0.0000	37.6653	0.0001
South Africa	40.3737	0.0021	26.8797	0.0069
Sudan	34.9548	0.0116	23.2218	0.0250
Swaziland	40.7960	0.0018	22.2691	0.0345
Tanzania	31.6320	0.0304	18.0922	0.1264
Togo	55.0559	0.0000	35.6228	0.0003
Uganda	70.0916	0.0000	56.1124	0.0000
Zambia	42.8817	0.0009	35.3085	0.0003
Zimbabwe	56.3430	0.0000	40.5655	0.0000

**MacKinnon-Haug-Michelis (1999) p-values

Table 9: Estimation Result of the Johansen-Fisher Individual Cross-Sectional Cointegration

Individual cross section results

Cross Section	Trace Test Statistics	Prob.**	Max-Eign Test Statistics	Prob.**
Hypothesis of at most 1 cointegration relationship				
Angola	18.5570	0.0167	18.4875	0.0101
Benin	13.8122	0.0882	12.0419	0.1091
Botswana	7.1610	0.5590	6.9949	0.4898
Burkina Faso	22.3309	0.0040	13.6055	0.0633
Burundi	13.7396	0.0904	11.6402	0.1249
Cameroon	13.7313	0.0906	12.3930	0.0967
Cape Verde	56.4521	0.0000	52.0313	0.0000
Central Africa...	9.0240	0.3632	9.0148	0.2849
Chad	23.8168	0.0022	18.5768	0.0098
Comoros	16.1153	0.0403	13.2148	0.0727
Democratic R...	7.2132	0.5530	6.5151	0.5480
Equatorial Gu...	25.6756	0.0011	17.0248	0.0178
Eritrea	22.1777	0.0042	12.9716	0.0792
Ethiopia	12.9812	0.1155	9.2704	0.2643
Gabon	8.9141	0.3734	7.3739	0.4459
Gambia	10.5972	0.2375	9.9768	0.2135
Ghana	12.3375	0.1415	9.4203	0.2528
Guinea	13.0095	0.1145	7.8493	0.3942
Guinea-Bissau	5.1086	0.7972	3.8414	0.8757
Ivory Coast	9.4775	0.3230	8.4648	0.3334
Kenya	21.7624	0.0050	18.0852	0.0119
Lesotho	13.8696	0.0866	11.2817	0.1407
Liberia	14.7387	0.0648	14.6994	0.0427
Madagascar	15.2624	0.0542	10.7621	0.1665
Malawi	7.3592	0.5362	6.1151	0.5985
Mali	15.2379	0.0546	10.7726	0.1660
Mauritania	19.9355	0.0100	11.4184	0.1344
Mauritius	8.5469	0.4089	8.4674	0.3332
Mozambique	16.6756	0.0331	12.4005	0.0965
Namibia	11.0907	0.2060	10.7473	0.1673
Niger	12.3879	0.1393	9.6859	0.2334
Nigeria	20.1938	0.0091	14.6207	0.0439
Republic of th...	17.9098	0.0212	9.5695	0.2418
Rwanda	12.1810	0.1485	11.0738	0.1505
Sao Tome an...	14.2352	0.0767	12.0377	0.1092
Senegal	10.3938	0.2517	9.9817	0.2131
Sierra Leone	12.0855	0.1529	11.7192	0.1216
Somalia	16.1160	0.0403	8.6501	0.3164
South Africa	13.4940	0.0979	8.9126	0.2935
Sudan	11.7330	0.1702	9.2516	0.2658
Swaziland	18.5269	0.0169	12.2730	0.1008
Tanzania	13.5398	0.0965	8.8725	0.2969
Togo	19.4332	0.0121	14.8312	0.0406
Uganda	13.9792	0.0835	13.9155	0.0567
Zambia	7.5731	0.5121	6.6917	0.5262
Zimbabwe	15.7775	0.0453	13.6776	0.0617

**MacKinnon-Haug-Michelis (1999) p-values

Table 10: Estimation Result of the Johansen-Fisher Individual Cross-Sectional Cointegration

Individual cross section results

Cross Section	Trace Test Statistics	Prob.**	Max-Eign Test Statistics	Prob.**
Hypothesis of at most 2 cointegration relationship				
Angola	0.0696	0.7920	0.0696	0.7920
Benin	1.7703	0.1833	1.7703	0.1833
Botswana	0.1661	0.6836	0.1661	0.6836
Burkina Faso	8.7254	0.0031	8.7254	0.0031
Burundi	2.0994	0.1474	2.0994	0.1474
Cameroon	1.3383	0.2473	1.3383	0.2473
Cape Verde	4.4208	0.0355	4.4208	0.0355
Central Africa...	0.0093	0.9230	0.0093	0.9230
Chad	5.2400	0.0221	5.2400	0.0221
Comoros	2.9005	0.0885	2.9005	0.0885
Democratic R...	0.6981	0.4034	0.6981	0.4034
Equatorial Gu...	8.6508	0.0033	8.6508	0.0033
Eritrea	9.2060	0.0024	9.2060	0.0024
Ethiopia	3.7108	0.0541	3.7108	0.0541
Gabon	1.5401	0.2146	1.5401	0.2146
Gambia	0.6204	0.4309	0.6204	0.4309
Ghana	2.9172	0.0876	2.9172	0.0876
Guinea	5.1602	0.0231	5.1602	0.0231
Guinea-Bissau	1.2673	0.2603	1.2673	0.2603
Ivory Coast	1.0127	0.3143	1.0127	0.3143
Kenya	3.6772	0.0552	3.6772	0.0552
Lesotho	2.5879	0.1077	2.5879	0.1077
Liberia	0.0393	0.8428	0.0393	0.8428
Madagascar	4.5002	0.0339	4.5002	0.0339
Malawi	1.2441	0.2647	1.2441	0.2647
Mali	4.4653	0.0346	4.4653	0.0346
Mauritania	8.5171	0.0035	8.5171	0.0035
Mauritius	0.0795	0.7780	0.0795	0.7780
Mozambique	4.2751	0.0387	4.2751	0.0387
Namibia	0.3434	0.5579	0.3434	0.5579
Niger	2.7021	0.1002	2.7021	0.1002
Nigeria	5.5731	0.0182	5.5731	0.0182
Republic of th...	8.3403	0.0039	8.3403	0.0039
Rwanda	1.1072	0.2927	1.1072	0.2927
Sao Tome an...	2.1975	0.1382	2.1975	0.1382
Senegal	0.4122	0.5209	0.4122	0.5209
Sierra Leone	0.3663	0.5450	0.3663	0.5450
Somalia	7.4659	0.0063	7.4659	0.0063
South Africa	4.5814	0.0323	4.5814	0.0323
Sudan	2.4814	0.1152	2.4814	0.1152
Swaziland	6.2539	0.0124	6.2539	0.0124
Tanzania	4.6674	0.0307	4.6674	0.0307
Togo	4.6020	0.0319	4.6020	0.0319
Uganda	0.0637	0.8008	0.0637	0.8008
Zambia	0.8815	0.3478	0.8815	0.3478
Zimbabwe	2.0999	0.1473	2.0999	0.1473

**MacKinnon-Haug-Michelis (1999) p-values

Granger Causality Tests

In order to test for causality between unemployment and labor force participation rate, the following equations are applied by utilizing a specification of 1 lag based on AIC criteria.

Table 11: Pairwise Granger Causality Test

Null Hypothesis	Obs.	P-values
MLFR does not Granger cause UNER	1426	0.6868
UNER does not Granger cause MLFR		0.0096
FLFR does not Granger cause UNER	1426	0.3811
UNER does not Granger cause FLFR		0.0043
FLFR does not Granger cause MLFR	1426	0.0387
MLFR does not Granger cause FLFR		0.0000

Additionally, a Granger causality test for panel data was computed for the variables under consideration with a specification of 1 lag. Table 8 displays the result of the causality test between the UNER and the explanatory factors (MLFR and FLFR). The findings rejected the null hypothesis that UNER does not cause MLFR, with a p-value of 0.0096, and failed to reject the null hypothesis that UNER does not cause MLFR, with a p-value of 0.6868. The results of the causality test are made obvious, with a broad conclusion that there is a one-way (uni-direction) causality relationship between UNER and MLFR. The results also reject the null hypothesis that UNER does not Granger cause FLFR with a p-value of 0.0043 and fail to reject the null hypothesis that FLFR does not Granger cause UNER with a p-value of 0.3811. There is no reverse causation between the variables; it is unidirectional. On the other hand, the result shows bidirectional causal relation rejecting the null hypothesis that both MLFR does not Granger cause FLFR and FLFR does not Granger cause MLFR, with p-values of 0.0000 and 0.0387, respectively.

Regression Results

The pooled OLS, fixed effect, and random effect estimation approaches are among the instruments utilized in assessing the link between unemployment and labor force participation rates in 46 sub-Saharan African nations during the period 1991–2022. The pooled OLS delivered efficient and consistent parameter estimations if the individual effect in a cross-section or time-specific effect does not present (Park, 2001). Both fixed effect and random effect models are utilized to account for the reality that the panels or countries may be heterogeneous. The fixed effect model implies that heterogeneity is not random and consequently alters the model to eliminate heterogeneity. The random effect, however, assumes the heterogeneity is random and so captures it with the random error. The table below provides the results of the pooled OLS regression.

Table 12: Pooled OLS Regression Result
Dependent Variable: UNER

Variables	Coefficient	t-statistics	P-values
C	28.96778	25.21439	0.0000
MLFR	-0.127175	-9.188271	0.0000
FLFR	-0.186073	-8.513082	0.0000
R-squared	0.285492	Mean dependent var	8.162452
Adjusted R-squared	0.284519	S.D. dependent var	6.677718
S.E. of regression	5.648423	Akaike info criterion	6.302666

P-value <0.05

Table 13: The Result of Fixed Effect Model

Dependent Variable: UNER

Variables	Coefficient	t-statistics	P-values
C	11.69176	11.97598	0.0000
MLFR	-0.029985	-2.565529	0.0104
FLFR	-0.024903	-1.936452	0.0530

R-squared	0.960169	Mean dependent var	8.162452
Adjusted R-squared	0.958854	S.D. dependent var	6.677718
S.E. of regression	1.354540	Akaike info criterion	3.476865

P-value<0.05

To select the most acceptable model from the common effect (POLS) and fixed effect models, we would apply the Chow test to discover the model that is most suitable for predicting the panel data.

Table 14: Chow Test

Effect Test	Statistic	d.f	p-values
Cross-section F	536.005098	(45, 1424)	0.0000
Cross-section chy-square	4249.578069	45	0.0000

Hypothesis:
Select CE (p>0.05)
Select FE (p<0.05)

Since the p-value is less than 0.05, we reject the null hypothesis and accept the alternative hypothesis, which implies that the fixed effect model is the right model between the common effect model and the fixed effect model. The next step is to run the random effect test and compare it with the fixed effect test by utilizing the Hausman test and select the suitable one among them.

Table 15: The Result of Random Effect Model

Dependent Variable: UNER

Variables	Coefficient	t-statistics	P-values
C	12.31574	9.707668	0.0000
MLFR	-0.036288	-3.156880	0.0016
FLFR	-0.028513	-2.229555	0.0549

R-squared	0.014178	Mean dependent var	0.347096
Adjusted R-squared	0.012836	S.D. dependent var	1.368086
S.E. of regression	1.359278	Sum squared resid	2714.177

P-value<0.05

Table 16: The Result of Hausman Test

Test Summary	Chi-sq. Statistic	P-value
Cross-section Random	12.294770	0.0021

Hypothesis

H_o : Select CE (P>0.05)

H_1 : Select FE (P<0.05)

Since the result of the Hausman specification test (Hausman, 1978) shows that the P-value is 0.0021, which is less than the 5% level of significance, the null hypothesis is rejected and the alternative hypothesis is accepted, which says that the fixed-effect model is the proper model.

However, the R-squared and the modified R-square (0.960169, 0.958854), respectively, of the model exhibit a superior match compared to the other estimations of the model.

Regarding this, the fixed effect model is 5% statistically significant on male labor participation rate and adversely explained the dependent variable (unemployment rate). If male labor force participation rate increases by 1 unit, then the unemployment rate reduces by the value of the coefficient (-0.0299). Therefore, the labor force rate has a negative influence on unemployment in sub-Saharan African countries.

And additionally, it is 10% statistically significant on the female labor force rate (FLFR) and is adversely explained by the dependent variable (UNER). If the female labor force rate increases by 1 unit, then the unemployment rate reduces by the value of the coefficient (-0.249).
This is consistent with the findings of a similar study by Nicholas and Ibrahim (2017), which found that there is a relationship between unemployment and labor force participation rates, while the impact of unemployment on labor force participation is negative, indicating the prevalence of the discouraged worker effect across the US.

CONCLUSION

After utilizing panel data analysis approaches, including unit root tests, panel cointegration methods, Granger causality analysis, and the fixed effect model, the relationship between unemployment and labor force participation rates in Sub-Saharan African nations can be determined as follows:

(i). Long-Term link: Panel cointegration analysis reveals the presence of a long-term equilibrium link between unemployment and labor force participation rate in various Sub-Saharan African nations. So, changes in one variable may affect the other over time.

(ii). In a Granger causality analysis of unemployment and labor force participation rates in Sub-Saharan African countries, considerable causation was discovered between unemployment and both male and female labor force participation rates, but only in one direction. Additionally, bidirectional causality is demonstrated between male and female labor force participation rates. These findings show complex linkages between unemployment and labor force participation rates, indicating potential gender-specific dynamics in the region.

(iii). The fixed effect model 5% significantly affects male labor participation rate, negatively influencing unemployment rate in sub-Saharan African countries, with an increase in labor force participation reducing unemployment. The female labor force rate (FLFR) is significantly impacted by the dependent variable (UNER), with a 10% increase in FLFR leading to a -0.249 reduction in unemployment.

In general, the analysis suggests a robust long-term relationship between unemployment and labor force participation rates in Sub-Saharan African countries, with labor force participation playing a significant role in influencing unemployment levels, emphasizing the importance of policies targeting labor market participation to address unemployment challenges.

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