Causality between economic growth and unemployment in East African countries

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Abstract

This study focuses on the factors determining economic growth and unemployment in East African countries from 1990 to 2020. Panel data was analysed using descriptive statistics. Breusch and Pagan Lagrangian multiplier test and Pesaran-Shin unit-root tests were employed. In addition, fixed effects and random-effects GLS regression models were utilised. The Granger causality test, which employs the Panel VECM model, evaluated the direction of causality. The Panel VECM model demonstrated that economic growth impacts unemployment in both the short and long term; however, unemployment does not Granger-cause economic growth. The government's policies should prioritise promoting economic development and reducing unemployment, as this will inevitably result in a decrease in unemployment. Efforts to combat unemployment that do not prioritise economic development will be less effective. Unemployment reduction will be more effective because of initiatives to stimulate economic development.

Keywords: Determinants of economic growth, Granger causality, Unemployment, East African countries.

Introduction

Mwasha (2012) asserts that the integration of East African countries offers multiple benefits for member states, including increased private investment stemming from an expanded market, enhanced economic growth, broader market opportunities due to a larger population base, and job creation for the workforce. Unemployment is conceptualized in various ways within the literature. Aiyedogbon et al. (2012) characterise it as the portion of the labour force that is ready for employment yet has not engaged in work for a minimum of 39 hours in the week prior to the survey. Osemengbe et al. (2013) define it as the state of individuals lacking employment, while the International Labour Organisation (ILO) includes anyone who has not engaged in work for more than an hour during the reference period but is actively pursuing job opportunities (Msigwa et al., 2013). The incremental increase in the production of commodities and services over time is frequently used to describe economic growth (Kimberly, 2018). Economic growth is defined by Raisova and Durcova (2014) as the increased capacity of an economy to produce products and services in a progressive manner over time. Babatunde (2018) defines it as a rise in the economic value of a country's goods and services, typically measured by gross domestic product (GDP).

Similarly, Alina (2012) views economic growth as the progression of national economies, reflected in higher GDP per capita.

Theoretical Perspective

Okun's Theory of Economic Growth and Unemployment

Developed by Arthur Okun in 1960, this theory explores the relationship between a nation's economic growth and unemployment rates. Federal Reserve Bank of St. Louis argue that Okun's estimates the reduction in economic output that occurs when unemployment exceeds its natural rate. The theory highlights a direct positive association between output and employment, emphasizing that total output depends on the labour engaged in production. Employment, defined as the active labour force excluding the unemployed, results in an inverse relationship between output and unemployment, assuming a constant labour force (Nagel, 2015).

Okun's "rule of thumb" state that a stable unemployment rate requires real GDP to grow at a rate equal to the combined growth rates of the labour force and productivity. To reduce unemployment, economic growth must surpass its potential rate (Ojima, 2019). Contemporary interpretations suggest that lowering unemployment by 1% generally requires real GDP to grow approximately 2 percentage points above the potential GDP growth rate. For example, if the potential GDP growth rate is 2%, achieving a 1% decrease in unemployment would necessitate real GDP growth of about 4% (Soylu et al., 2018).

Khrais (2016) observes that while Okun's theory has predominantly been tested within the United States, numerous methodologies have emerged to monitor unemployment. Okun's initial postulation is the vacuum between actual and potential economic outcome. Subsequent studies, such as those by the Kansas City Federal Reserve, have explored variations of the theory, including the "gap version," which examines differences between actual and potential output.

Chand et al. (2017) highlight the theory's continued relevance as a straightforward and effective framework for analyzing the link between economic growth and employment. A key strength lies in its simplicity, which suggests that a 1% reduction in unemployment is typically associated with approximately 2% faster-than-expected economic growth. However, its predictive reliability is limited by evolving economic dynamics, including phenomena like jobless recoveries and financial crises, which indicate that Okun's Law is subject to temporal shifts and may not always yield precise predictions.

The stability of Okun's coefficients has been a topic of debate. Blanchard (2018) contends that these coefficients have exhibited varying degrees of stability across countries and have generally declined over time due to changes in economic conditions and measurement techniques. The concept of "full employment," originally equated by Okun to a 4% unemployment rate, has also evolved. Influenced by Keynes and Beveridge, who defined full employment as a state where only frictional unemployment persists, the understanding of this term has shifted over time (Dubina, 2017). Despite its practical utility, Okun's theory does not explain the fundamental drivers of economic growth and unemployment or how these factors interact, limiting its effectiveness in forecasting these economic outcomes. Findings indicate that Okun's coefficients have diminished in advanced economies and are often negligible or insignificant in developing nations. Blanch flower (2019) argues that the traditional Okun coefficient may not serve as a reliable policy tool, as it fails to fully account for the impacts of wage and inflation dynamics.

Theoretical Review

Khrais (2016) observes that while Okun's theory has predominantly been tested within the United States, numerous methodologies have emerged to monitor unemployment. Okun's initial analysis emphasized the vacuum between actual and economic outcome. Subsequent studies, such as those by the Kansas City Federal Reserve, have explored variations of the theory, including the "gap version," which examines differences between actual and potential output. Chand et al. (2017) highlight the theory's continued relevance as a straightforward and effective framework for analyzing the link between economic growth and employment. A key strength lies in its simplicity, which suggests that a 1% reduction in unemployment is typically associated with approximately 2% faster-than-expected economic growth. However, its predictive reliability is limited by evolving economic dynamics, including phenomena like jobless recoveries and financial crises, which indicate that Okun's Law is subject to temporal shifts and may not always yield precise predictions. The stability of Okun's coefficients has been a topic of debate. Blanchard (2018) contends that these coefficients have exhibited varying degrees of stability across countries and have generally declined over time due to changes in economic conditions and measurement techniques.

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Empirical Review

Economic growth plays a vital role in fostering employment, as increased economic activity drives job creation (Bashier & Wahban, 2013). Research into the validity and consistency of Okun's Law has raised concerns about how economic growth influences labour market outcomes (Dopke, 2015). Zagler (2004) investigated economic growth and unemployment in 15 OECD countries between 1970 and 1999. Employing the Granger causality test, the study assessed the predictiveness of economic growth on unemployment. The findings revealed a bi-directional causal correlation amongst the variables, with variations and direction across countries. In some nations, economic growth had a stronger influence on unemployment, while in others, unemployment exerted a greater effect on economic growth. Labour market institutions and government policies significantly shaped these dynamics. Countries with rigid labour market structures tended to exhibit a stronger relationship from unemployment to economic growth, whereas those with flexible labour markets displayed a stronger relationship between economic growth and unemployment.

According to Okun (1962), a 1% reduction in unemployment rates corresponds to 3% increase in real GDP, and so forth. This relationship underscores the role of economic growth in generating employment and reducing unemployment. Moreover, economic growth is a central policy objective for governments, signifying improved living standards, enhanced quality of life, and a reduction in poverty (Hala et al., 2021). Economic growth not only creates employment opportunities but also increases income levels and promotes overall economic welfare. Zagler (2004) further highlighted the influence of institutional factors, noting that labour market rigidity tends to strengthen the link between unemployment and economic growth, while more flexible labour markets amplify the effect of economic growth on unemployment.

Methodology

This study adopted a quantitative research approach, which is particularly well-suited for addressing research questions that involve numerical data and statistical analysis (Williams, 2011). Quantitative methods enable the systematic collection and evaluation of data, facilitating hypothesis testing and pattern identification, as outlined by Amin (2005). By utilizing numerical data and statistical tools, this methodology provides a structured framework for analyzing key variables related to economic growth and unemployment.

To complement the quantitative approach, an ex-post facto research design was employed. This design was chosen for its focus on analyzing pre-existing data, specifically panel data covering the period from 1990 to 2020. Ex-post facto research is tailored to examine existing conditions and investigate potential causal relationships between variables (Booth, 2001). Its strengths lie in its ability to utilize historical data to uncover long-term trends and infer causal relationships, making it particularly effective for studying the determinants of economic growth and unemployment (Dixon-Woods et al., 2007).

By employing the ex-post facto design, the study developed a predictive model to analyze the long-term causal relationships between economic growth and unemployment in the East African Community (EAC). This methodological approach offers valuable insights into how historical patterns can inform future outcomes and guide policy decisions.

Nature and Sources of Data

This study utilized secondary data obtained from reputable databases and institutions to ensure reliability and comprehensiveness. The primary data sources included the following:

1) World Bank Development Indicators (WDI): This resource provides a broad range of global economic, social, and environmental data. It was a key source for acquiring economic indicators relevant to the study.
2) African Development Indicators (ADI): Focused on Africa's economic and social development, this database was integral for conducting a regional analysis specific to the East African Community.
3) United Nations Conference on Trade and Development (UNCTAD): UNCTAD's database, which offers insights on international trade, investment, and development, was crucial for evaluating foreign direct investment and trade-related variables.
4) International Monetary Fund (IMF): The IMF provides macroeconomic data, including inflation rates and other key indicators, essential for analyzing the interplay between economic growth and unemployment.
5) Organisation for Economic Co-operation and Development (OECD): Data from the OECD on inflation and other economic metrics were incorporated into the study's analysis.

Table 1: Indicators

Variables	Descriptions	Variable Measurement	Source of data
GDP	GDP (Economic growth measure)	Annual % change of GDP	World development indicator (WDI)
UE	Unemployment	% of total labour force	World development indicator (WDI)

Model Specification

In this study the model specification is as follows;

$$UNEMP_1(t) = \sum_{j=1}^{p} {}_{A1}\ jUNEMP_1(t-j) + \sum_{j=1}^{p} A_{2,j} GDPGR_2(t-j) + \ell_1(t) \qquad (1)$$

Whereby p is the maximum number of lagged observations included in the model (the model order), the matrix A contains the coefficients of the model (i.e., the contributions of each lagged observation to the predicted values of $UNEMP_1$ (t) and $GDPGR_2$ (t), and $E1$ is residual (prediction error) for each time series. If the variance of ℓ_1 is reduced by the inclusion of the $E.G_2(t)$ terms in the equation, then it is said that $GDPGR_2$ *(t)* (or $UNEMP_1$ *(t)*) Granger-(GDPGR)-causes $UNEMP_1$ *(t)* (or $GDPGR_2$ *(t)*). In other words, $GDPGR_2$ *(t)* GDPGR-causes $UNEMP_1$ *(t)* if the coefficients in A_2 are jointly and significantly different from zero. This can be tested by performing an F-test of the null hypothesis that $A_2 = 0$, given assumptions of covariance stationarity on $UNEMP_1$ *(t)* and $GDPGR_2$ *(t)*. The magnitude of a GDPGR-causality interaction can be estimated by the logarithm of the corresponding F-statistic.

Techniques of Data Analysis

The analysis techniques included; Vector Error Correction Model (VECM) for Granger causality.

Pre-Estimation tests

a. Normality test

Before proceeding with estimation, a normality test is conducted to determine whether the sample data originates from a normally distributed population. Normality is crucial for many statistical tests, including linear correlations and ANOVA, which assume a bell-shaped distribution of the data. In cases of small sample sizes, visual inspection alone may be insufficient for confirming normality. In such instances, a quantile-quantile (Q-Q) plot can be used to compare the data distribution against a theoretical normal distribution with equivalent mean and variance. Deviations from the regression line in this plot may suggest non-normality (Szekely & Rizzo, 2005).

b. Heteroscedasticity test

Typically conducted using a χ^2 test, this procedure involves analyzing the residuals in relation to the fitted values and independent variables. Ordinary Least Squares (OLS) regression operates under the assumption that errors maintain constant variance, a condition referred to as homoscedasticity. When this assumption is violated, and the error variance varies across levels of an independent variable, the phenomenon is known as heteroscedasticity (Jacquier et al., 1994).

c. Balanced panel test

This test shows repeated observations of variables over time for multiple units (Frees, 2004). Panel data combines both time-series and cross-sectional dimensions, enabling the analysis of variations over time and across entities. The classification of a dataset as time-series, panel, or cross-sectional depends on the identification of a unique time-related field within the data (Baltagi, 2008).

d. Trend Analysis

Trend analysis is a statistical technique used to project future movements of a variable based on historical data. By examining historical patterns, such as price changes and trade volumes, trend analysis aims to forecast long-term market directions (Bayazit, 2015). This method involves evaluating current trends to predict future trajectories, offering a comparative analysis of whether ongoing trends, such as gains in specific market sectors, are likely to continue and how they may influence other areas (Guclu, 2018). Trend analysis helps identify and monitor trends, such as bull markets, until indicators suggest potential reversals (Caloiero et al., 2018). While it provides valuable insights for investors by aligning with prevailing trends, it is important to note that trend analysis relies on historical data and does not ensure prediction accuracy (Caloiero et al., 2018).

Post-Estimation tests

a. Hausman test

The Hausman test is a statistical tool used in panel data analysis to evaluate the appropriateness of model specifications, specifically distinguishing between fixed effects and random effects models. It examines the correlation between the unique errors of the model and the regressors, thereby aiding in the selection of the most suitable model for the dataset.

- **Null Hypothesis (H_0):** The random effects model is appropriate, implying no correlation between the unique errors and the regressors.
- **Alternative Hypothesis (H_1):** The fixed effects model is more appropriate, indicating a correlation between the unique errors and the regressors.

The Hausman test involves comparing the parameter estimates from fixed effects and random effects models to detect any potential misspecification. A significant test statistic suggests that the random effects model may be biased, leading to the recommendation of the fixed effects model as the preferred option (Vogt, 2005).

b. Normality of the error term

The assumption of normality for the error term is a cornerstone in many statistical techniques, particularly linear regression. This assumption underpins the validity of inferential procedures by positing that the disturbance or error term follows a normal distribution. Notably, the normality assumption is not tied to sample size but is based on the cumulative effect of multiple predicted errors affecting a single observation (Gujarati, 2002).

Results

a. Fixed Effects Model

The fixed effects model was employed to address potential biases and control for time-invariant variables, such as gender and culture, which are inherently excluded from the analysis (Torres, 2007). The fixed effects model was preferred over the random effects model due to the latter's requirement for a larger number of cross-sections relative to the number of coefficients being estimated.

b. Diagnostic Test

Panel Unit Root Test

To evaluate the stationarity of the variables, a panel unit root test was conducted. Stationarity indicates that a variable does not exhibit a unit root and that its statistical properties remain stable over time (Breitung & Das, 2005). The presence of unit roots can lead to spurious results in regression analysis. The Im-Pesaran-Shin (IPS) panel unit root test was chosen for its efficacy in handling unit roots in panel data and analyzing long-term causal relationships with fewer observations (Im, Pesaran, & Shin, 1997). The null hypothesis for the IPS test is:

- **H_0:** All panels contain unit roots, indicating non-stationarity.
- **H_1:** Some panels are stationary.

Variables with p-values exceeding 0.05 are deemed non-stationary and may require transformation or differencing to achieve stationarity (Obwona, 1996; Obwona, 1998).

Tests for Auto-correlation

To identify autocorrelation, the study utilized Baltagi and Wu LBI test quite apart from modified Durbin-Watson test. Both tests are well-suited for detecting autocorrelation in panel data. Furthermore, the Kmenta-Parks method was employed due to its versatility in handling both fixed and random variables that may vary over time, effectively addressing clustering errors.

Cointegration Test

Prior to multivariate analysis, a cointegration test was conducted to assess long-run and short-run relationships among the time series data. The test adhered to procedures outlined by Pedroni (1999, 2004) and Westerlund (2007). Cointegration testing is critical for non-stationary time series data (Osuala & Onyeike, 2013). The Johansen's Maximum Likelihood

Method was employed, alongside the test provided by Kao (1999). The hypotheses for the cointegration test are:

- **H_0:** No cointegration.
- **H_1:** All panels are cointegrated.

Table 2: The Summary Statistics for the Series of the Dataset

Variable	Mean	Std. Dev.	Min	Max	Observations
econom~h overall	4.330576	6.316281	-50.24807	35.22408	N = 155
between	2.052349	1.157427	6.340775		n = 5
within	6.041839	-51.37534	34.0968		T = 31
unempl overall	4.737553	3.686136	.871	13.01	N = 155
between	4.060553	2.268194	11.96668		n = 5
within	.5581004	3.34036	7.121053		T = 31

Economic growth in the East African Community (EAC) over 31 years recorded an overall mean of 4.33%, with a standard deviation of 6.32%. The highest GDP growth rate recorded was 35.22%. The GDP growth rate across the five EAC countries showed a deviation of 2.05%, with a mean range between 2.28% and 6.38%. The GDP growth varied between -1.71% and 10.37%, with the highest rate being 34.10%. These results indicate significant variations in economic growth rates among EAC countries, with Rwanda exhibiting the most variability (Table 2).

Unemployment data shows an overall average rate of 4.74% with a high standard deviation of 3.69%, indicating unstable trends. The minimum rate was 0.871%, and the maximum was 13.01%. Between the EAC countries, the standard deviation was 4.07%, with minimum and maximum rates of 2.27% and 11.97%, respectively. This instability in unemployment trends is evident within the country data but not in the general data for the 31-year period. The small deviation within the 31 years (0.56%) and the difference between the maximum (7.12%) and the "between" country data comparisons suggest varying unemployment trends, particularly with Rwanda having a significantly higher rate compared to other EAC countries. ANOVA results indicate that Rwanda's average unemployment rate is more than three times higher than other countries.

Table 3: ANOVA comparisons for Unemployment data of EAC countries

Country	Mean	Std. Dev.	Freq.
Uganda |	3.2379193	.5503337	31
Kenya |	3.2325	.62661493	31
Tanzania |	2.9824758	.47434751	31
Rwanda |	11.966678	22356948	31
Burundi |	2.2681935	.79272182	31
Total |	4.7375532	3.6861362	155

Test for Normality

The study variables employed in the regression models were first tested for their data normality to ascertain their suitability and to avoid spurious results. This was tested using Kurtosis and Skewness statistics and results are presented in tables 4A to 4F.

Table 4A: Normality Test for Study Variables; All the Five Countries

Variable |	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
economicgr~h |	155	0.0000	0.0000	.	0.0000
unempl |	155	0.0000	0.5688	25.90	0.0000

Table 4B: Normality Test for Study Variables; Uganda

Variable |	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
economicgr~h |	31	0.2684	0.8018	1.38	0.5017
unempl |	31	0.0345	0.1070	6.45	0.0398

Table 4C: Normality Test for Study Variables; Kenya

Variable |	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
economicgr~h |	31	0.5383	0.4086	1.13	0.5683
unempl|	31	0.0000	0.0002	25.78	0.0000

Table 4D: Normality Test for Study Variables; Tanzania

Variable |	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
economicgr~h |	31	0.0393	0.8672	4.39	0.1112
unempl |	31	0.0761	0.4146	4.03	0.1331

Table 4E: Normality Test for Study Variables; Rwanda

Variable |	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
economicgr~h |	31	0.0000	0.0000	28.48	0.0000
unempl |	31	0.0000	0.0000	36.40	0.0000

Table 4F: Normality Test for Study Variables; Burundi

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
economicgr~h	31	0.0232	0.6341	5.22	0.0735
unempl	31	0.3236	0.0000	14.06	0.0009

Table 5: ***Heteroscedasticity Test Results***

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of economicgrowth

         chi2(1)      =   298.23
         Prob > chi2  =   0.0000
```

The results in Table 5 revealed the presence of heteroscedasticity, as indicated by the P-value (Prob > chi2 = 0.0000), which is significantly less than 0.05. This suggests that the residual variances are not constant. To address this issue, the data was log-transformed before running the regression models. The heteroscedasticity test was then conducted on the log-transformed data, and the final results are presented in Table 6.

Table 6: ***Heteroscedasticity Test Results***

```
. hettest lneconomicgrowth2

Breusch-Pagan / Cook-Weisberg test for heteroskedastici
         Ho: Constant variance
         Variables: lneconomicgrowth2

         chi2(1)      =     3.40
         Prob > chi2  =   0.0651
```

The results in Table 6 indicated that the issue of heteroscedasticity was resolved, as the P-value (Prob > chi2 = 0.0651) is now greater than 0.05. This suggests that the residual variances are constant, making the data suitable for regression models.

Stationarity Test

Stationarity implies that a variable with an integration order of zero does not possess a unit root (Breitung & Das, 2005). The existence of a unit root can result in misleading regression outcomes and unreliable predictions. Consequently, it is essential to conduct stationarity tests prior to running regression models to ensure the temporal accuracy of the data and to reduce the likelihood of spurious results (Breitung & Das, 2005).

In this study, the Levin-Lin-Chu Unit Root Test was employed using STATA to ascertain the stationarity of the variables and to confirm the absence of unit roots (Obwona, 1996). Variables with P-values exceeding 0.05 and t-statistics less than 2 were identified as non-stationary (Obwona, 1998). As recommended by Obwona (2001), non-stationary variables were converted to their first differences. Accordingly, data transformation or differencing was applied as necessary to achieve stationarity before implementing the regression model (Chetty & Narang, 2017). The outcomes of the stationarity tests are detailed in Tables 7 through 16.

Table 7: Stationarity Test for Economic Growth

Im-Pesaran-Shin unit-root test for economic growth

	Statistic	p-value	Fixed-N exact critical values 1%	5%	10%
t-bar	-3.7384		-2.430	-2.160	-2.020
t-tilde-bar	-2.9924				
Z-t-tilde-bar	-4.3883	0.0000			

The unit root test results in Table 7 reveal that the economic growth variable is stationary with the P-value of 0.0000 (<1%) and t-statistic value of -4.3883 (>2).

Table 8: Stationarity Test for Unemployment

Im-Pesaran-Shin unit-root test for Unempl

	Statistic	p-value	Fixed-N exact critical values 1%	5%	10%
t-bar	0.7791		-2.430	-2.160	-2.020
t-tilde-bar	0.5505				
Z-t-tilde-bar	5.6357	1.0000			

The unit root test results in Table 8 indicate that the unemployment variable is non-stationary with the P-value of 1.000 (>5%) and t-statistic value of 0.0974 (<2). The data for this unemployment variable was set to its first difference and a test for stationarity was run again (Chetty & Narang, 2017). The stationarity results of the level one differenced unemployment variable were still non-stationary and so the data was set to the second difference and passed the stationarity test as indicated in table 8.

Table 8: Stationarity Test for Unemployment (second difference)

```
. xtunitroot llc unempl_d2, trend

Levin-Lin-Chu unit-root test for unempl_d2
------------------------------------------
Ho: Panels contain unit roots                Number of panels  =      5
Ha: Panels are stationary                    Number of periods =     29

AR parameter: Common                         Asymptotics: N/T -> 0
Panel means:  Included
Time trend:   Included

ADF regressions: 1 lag
LR variance:     Bartlett kernel, 10.00 lags average (chosen by LLC)
------------------------------------------------------------------------
                    Statistic      p-value
------------------------------------------------------------------------
 Unadjusted t       -11.1514
 Adjusted t*         -4.6253        0.0000
------------------------------------------------------------------------
```

As indicated in Table 8, the unemployment variable is stationary at second level difference. The P-value of 0.0000 (<1%) and t-statistic value of -4.6253 (<2), satisfy the stationarity condition and so the data was deemed suitable for multivariate analysis. To determine the direction of causality between economic growth and unemployment, the researcher employed the Panel Vector Error Correction Model (P-VECM). Traditional correlation and regression analyses are insufficient for addressing causality, as they merely indicate association without establishing cause and effect. This limitation aligns with the commonly stated principle that correlation does not imply causation. Consequently, the regression results from earlier sections could not adequately resolve the causality question between these two variables (Winarno et at., 2020). The P-VECM was selected for its suitability in analyzing both short-term and long-term dynamics between economic growth and unemployment, even when the data is non-stationary, as highlighted by Lopez and Weber (2017). Unlike the Panel Vector Autoregression (P-VAR) model, the P-VECM accommodates the presence of non-stationary data, making it a more robust choice for this analysis.

The Granger causality approach was applied to test the null hypothesis (H_0) that unemployment does not Granger-cause economic growth against the alternative hypothesis (H_1) that unemployment does Granger-cause economic growth for at least one panel (identified by country code). Upon conducting the P-VECM analysis, the results allowed for the rejection of the null hypothesis at the conventional significance levels of 0.1, 0.05, and 0.001, indicating evidence of Granger causality in the relationship between unemployment and economic growth.

The results are presented in Table 9.

Table 9: Granger Causality between Economic Growth and Unemployment.

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------------------------------------------------------------
Optimal number of lags (BIC): 1 (lags tested: 1 to 8).
W-bar =          1.1345
Z-bar =          0.2127   (p-value = 0.8316)
Z-bar tilde =    0.0751   (p-value = 0.9402)
------------------------------------------------------------
```

H0: Unempl does not Granger-cause economic growth.
H1: Unempl does Granger-cause economic growth for at least one panel (ctycode).

The results from the P-VECM regression in Table 9 produced a p-value above 0.05, and so the null hypothesis is accepted, leading to a conclusion that in the East African countries, unemployment does not granger cause economic growth and so the opposite is true that economic growth granger cause unemployment.

Discussion of Findings

The study employed a Panel Vector Error Correction Model (P-VECM) to examine the causal relationship between economic growth and unemployment, capturing both short-term and long-term dynamics, consistent with the methodological framework outlined by Lopez and Weber (2017). The analysis incorporated the Granger causality approach to test the null hypothesis (H_0) that unemployment does not Granger-cause economic growth. The findings indicated that economic growth significantly influences unemployment in both the short and long run.

These results align with the conclusions of Niranjala (2019), who identified economic growth as a pivotal factor in addressing unemployment in Sri Lanka, linking persistent unemployment to insufficient economic growth. Similarly, Mosikari's (2013) study on South Africa, covering the period 1980–2011, reported a lack of causality between unemployment and economic growth, further highlighting the complex interplay between these variables across different contexts. Additional studies corroborating these findings include those by Hussain et al. (2010) in Pakistan (1972-2006), Kitov (2011) across the US, France, UK, Australia, Canada, and Spain, Soylu (2018) in Eastern Europe, Kreishan (2017), and Akeju and Olanipekun (2014) in Nigeria. However, the study's conclusions diverge from those of other scholars.

For instance, Sahin et al. (2013) in Turkey, Oye, Inuwa, and Muhammed (2011) in Nigeria, Akiri, Okunakpo, and Anebi-Atede (2015) in Nigeria, and Onwanchukwu (2015) in Nigeria found contrasting results. Dritsakis and Pavios (2016) asserted that unemployment, rather than economic growth, drives the economy in Nigeria. Additionally, Sibusiso and Hlalefang (2018) in South Africa, Soylu, Çakmak, and Okur (2018) in Eastern Europe, and Kukaj (2018) in the Western Balkans argued that unemployment negatively impacts GDP growth, thereby indicating that unemployment can lead to economic growth reductions.

Conclusions

Drawing from the study's findings and discussions, the following conclusions are established: Regarding the final objective, the evidence indicates that unemployment does not exert a causal influence on economic growth in either the short or long term. Instead, the analysis demonstrates that economic growth significantly drives changes in unemployment within the region. This highlights the pivotal role of GDP growth in shaping unemployment rates across the East African Community (EAC) countries during the 31-year period analyzed (1990–2020).

Recommendations

Based on the findings and conclusions of this study, the following policy recommendations are proposed:

1) To foster economic growth and reduce unemployment, government policies should prioritize strategies that drive economic growth, as this will inherently contribute to lowering unemployment rates. Attempts to address unemployment without a focus on stimulating economic growth are likely to yield limited success. Conversely, initiatives aimed at promoting economic growth are more effective in addressing both economic growth and unemployment challenges.
2) Governments within the East African Countries should adopt growth-oriented policies rather than those solely focused on job creation. While both approaches may appear to address similar objectives, the findings of this study suggest that emphasizing economic growth offers a more comprehensive solution to these interconnected economic issues. Specifically, prioritizing economic growth policies can effectively mitigate unemployment, whereas policies targeting unemployment alone are unlikely to meet the region's economic growth needs. This is underscored by the study's evidence that unemployment has not been a driver of economic growth over the past 31 years.

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