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Modeling the Unemployment Rate using the Panel ARDL

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Abstract

The purpose of this study is to investigate the effects of macroeconomic variables on the unemployment rate in North African countries. The analysis employed econometric techniques such as panel unit root tests, cointegration analysis, and model estimation. This model makes it possible to distinguish between the short-run effect and the long-run one. In this study, the short-term and long-term effects of economic growth on the unemployment rate were investigated using a combined autoregressive distributed lag (ARDL) panel approach.

The results show that there is a long-term relationship because the error correction parameter, or adjustment coefficient, is statistically significant and negative. In the short run, gross domestic product growth does negatively affect the unemployment rate; the effect is significant in the long run. On the other hand, the effect of labor force growth is significant in the short run. However, it is not significant in the long run. Finally, the results suggest that the effect of foreign direct investment on the unemployment rate is significant, both in the long run and in the short run.

***JEL codes:** E41, E52, C22.*

Keywords: Artificial Intelligence, Banking Industry, Financial Sector, Chat Bots, Customer Experience.

Introduction

Both the growth rate and the unemployment rate can be explained by Okun's law, which relates wage and price levels to the latter. The selection of a growth rate or level specification has implications. In fact, the model's equilibrium unemployment rate will be determined by this decision. The choice of specification is significantly influenced by the level of integration of the variables considered in the modeling. A study of the stationarity of the different variables used is very important.

This relationship between all variables is first estimated using annual panel data from 1991 to 2023. By using a Panel-ARDL estimation method, both the short and long term can be taken into account. In general, Okun's law's growth rate specification fits the short term, whereas the level specification fits the long term better. The non-stationarity of the variables under study will be helpfully addressed. In his research on the US economy, Okun demonstrated empirically that the unemployment rate and potential output were inversely correlated, contingent on labor force participation, length of employment, and productivity change [1, 2].

The idea that a larger workforce necessitates the production of more goods and services forms the theoretical foundation of the relationships Okun examined. When the real growth rate was high, he discovered, the unemployment rate decreased; when the real growth rate was low or even negative, he discovered, the unemployment rate rose.

The ratio of unemployed people actively looking for work or those who have been temporarily laid off to the total number of employed and unemployed people is commonly referred to as the unemployment rate. A high rate of unemployment is one of the traits of developing or impoverished nations. In every nation, public authorities have this as one of their top concerns. To gain a better understanding of this phenomenon, a theoretical investigation and modeling of the growth rate and the equilibrium unemployment rate are required.

Review of Theoretical Literature

According to Okun's law, a number of studies examine the connection between economic growth and unemployment. The relationship between economic growth, money supply, gross fixed formation, and formal employment was examined by Saungweme and Odhi- ambo in Zimbabwe [3]. The study employed formal employment as a dependent variable and the money supply, gross fixed formation, and economic growth as indecentdent variables. Formal employment is positively impacted by economic growth and gross capital formation, according to the study, which used the ARDL approach. Therefore, while the purchase of machinery in Zimbabwe increases production capacity, which in turn leads to the formal creation of jobs, economic growth in Zimbabwe also generates more jobs. Bande-Ramudo et al. used a structural VAR model, but they still got the same results [4]. In Tanzania, Suleiman et al. discovered contradictory findings [4]. Using the dynamic ordinary least squares (DOLS) methodology, the authors came to the conclusion that employment in Tanzania is inversely correlated with GDP and economic growth. In other words, employment declines as GDP and economic growth rise.

A different approach was taken by Sahnoun and Abden-Nadher, who contrasted developed and developing nations [5]. The authors looked at other factors like inflation, trade, and government size in addition to the relationship between unemployment and economic growth. Using panel data, the study discovered a negative relationship between unemployment, and both developed and developing nations' inflation, trade, and economic growth. The findings suggest that the likelihood of hiring one person is increased in both developed and developing nations when there is a low rate of inflation, a rise in trade, and economic expansion.

According to Bayar, a study conducted in emerging nations has demonstrated that the unemployment rate is lowered by gross domestic formation [6]. The study used panel data between 2001 and 2014. The factors influencing Jordan's unemployment rate between 1992 and 2015 were examined by Alrabba [7]. The ADF test was used to verify the stationarity and discovered that the variables were stationary at various levels. The VAR model was used to apply variance decomposition, Granger causality, and the impulsive response function. The study's conclusions demonstrated that private investment has a negative impact on Jordan's unemployment rate, which accounted for the overall 2.64% imbalances in the unemployment rate during the second period and the 1.58% imbalance during the fourth. Additionally, this weighting decreased until the ninth period, when the explanatory power of private investment for the forecast error in the unemployment rate could reach 1.34%.

A study conducted by Phiri for South African countries between 2000 and 2013 found a nonlinear equilibrium between unemployment and economic growth [8]. To do this, a momentum threshold autoregressive model was used. Makun and Azu examined how unemployment and economic growth interacted with the Fijian economy between 1982 and 2012 [9]. The analysis has shown that there is a long-term correlation between unemployment and economic growth. Ruxandra investigated the connection between unemployment and economic growth for the years after 2007 [10]. Okun's law has been found to be applicable to the Romanian economy. The literature also examines whether there is an asymmetry with regard to output unemployment, in addition to examining whether a relationship exists between output level and unemployment rate. Banda et al. also used a periodic time series data set for the years 1994–2012 to analyze the impact of eco- nomic development on South Africa's unemployment rate [11]. Using Johnson's Cointegration and Vector Error Correction Model, their research demonstrated a positive long-term re- patronship between economic development and unemployment. Long-term, this will result in higher unemployment, which will also be a reflection of economic expansion.

Imtiaz et al. conducted an empirical investigation into the factors influencing youth unemployment in Pakistan [12]. They used overpopulation, political unpredictability, a lack of investment, and the agriculture sector's backwardness as explanatory factors. They discovered that the current recession primarily affected young people (15–24 years old). The desire for improved employment conditions, policy evaluation, and an assessment of the justifications for supporting the provision of more advanced jobs for young people were also covered. The results showed that youth unemployment was significantly impacted by the explanatory variables. Mahmood et al. investigated the connection between various factors and unemployment [13]. First, autocorrelation, homoscedasticity, independence, and normality were discovered. Stepwise regression was used to choose the model using data spanning 1990 to 2010. The estimated results showed that unemployment was positively impacted by the labor force and negatively impacted by inflation.

Model Specification

In this study, we examine the relationship between growth and unemployment in the five countries that form North Africa (Algeria, Egypt, Morocco, Libya, Tunisia). The unemployment rate is affected by many economic variables, especially the country's gross domestic product growth, the labor force growth rate, the foreign direct investments inflow, gross fixed capital formation, the country's exports, the country's imports, the level of human development, inflation rate.

$$(UNE)_{it} = \alpha_0+\alpha_1(GDPg)_{it}+\alpha_2(LFg)_{it}+\alpha_3(FDI)$$

$$_{it}+\alpha_4(GFCf)_{it}+\alpha_5(EX)_{it}+\alpha_6(IM)_{it}+\alpha_7(INF)_{it}$$

where:

- **UNE** = Unemployment rate.
- **GDPg** = Gross domestic product growth. LFg = Labor force growth.
- **FDI** = Foreign direct investment. GFcf = Gross fixed capital formation. EX = total export as a % of GDP. IM = total import as a % GDP.
- **INF** = inflation rate as % of annual.

The above equations are for panel level where I represent cross-section data and t represents time-series data. The variables chosen in this paper complied with theories or hypothesis and their expected signs derived from the theories and previous studies. I used econometric techniques to test the data by using Panel Unit Root Test, Panel ARDL approach to co integration, PMG, MG and DEF estimators to comply with the objectives of the study.

Research Methodologies

In this research, I tested the selected data with Panel unit root test to identify the appropriate methodology to apply for the estimation process. The panel unit root test was derived from time series unit root tests, and the estimates are more consistent and efficient for panel unit root test to examines how the export and import of country that influence on unemployment rate and investigates the effects of Foreign direct investment on Unemployment , so the countries can learn to minise their unemployment rate.

Panel Unit Root Test

The Panel Unit Root Test was derived from time series unit root testing. Time series unit root tests lacked power in testing the difference of the unit root test from stationary alternatives. There are four most widely used panel unit root tests which are developed by Levin, Lin and Chu , I'm, Pesearan and Shin (1997-2003), Fisher type of ADF and PP tests. This step was suggested by Mestiri [14-16].

Levin, Lin and Chu (2002) Test

The nature of panel data has both cross-section and time-series dimensions. Levin et al considered a stochastic term (Yit) for i=1,.. n and t=1,. . . ,t [14]. when t or n is large and t is small and n is large, this test is one of the suitable test to apply to test the panel data. Normally all panel shares a common autoregressive parameter, and LLC augments the test with additional lags of the dependent variables. The following equation is to LLC regression model:

$$\Delta Y_{it} = \alpha Y_{it-1} + \sum_{j=1}^{p_i} \beta_i \Delta Y_{it-j} + X_{it}^* + \epsilon_{it}$$

In the above equation, ΔYit is the difference term of Yit and Yit−j is panel date where is exogenous variables such as individual time trend or country fixed effects, the assumption of LLC test is that ϵit, the error term is distributed independently across panel data and follows a stationary invertible autoregressive moving-average process for each panel. The null and alternative hypotheses are as below.

- **H0 :** βi = 0 for all i which means panel data has unit root test.
- **HA :** βi < 0 for all i which means panel data has no unit root test.

LLC test requires βi to be homogenous across i for this hypothesis and this homogeneity requirement become a disadvantages of LLC test. This implies that if the autoregressive parameters are same across panel, HA is restrictive, and t-statistics relied on pooled estimation can be described as.

$$t_\alpha^* = \frac{t_\alpha - (NT)S_N \bar{\alpha}^{-2} se(\bar{\alpha}) \mu_{mT}}{\sigma_{mT}}$$

Where α has standard normal distribution, t*α for standard t-statistics

- **se(α)=** standard error of α
- α^{-2} = error term
- **SN =** average standard deviation ratio
- **µmT** = adjustment term of the mean
- **σmT** = adjustment term of the mean

I'm, Pesaran and Shin (2003) Test

Im et al. suggested that T-bar statistics analyze the unit root test hypothesis for panel data which relies on the average of individual ADF t- statistics [17]. IPS test is more accurate than LLC test. For a sample having n groups and t time periods where i = 1, ... ,n and t = 1, ... ,t, the regression model of the conventional ADF test for panel unit root is as follows.

$$\Delta Y_{it} = \alpha_i + \beta_i Y_{it} + \sum_{j=1}^{p_i} \beta_j \Delta Y_{it-j} + \epsilon_{it}$$

The null and alternative hypotheses are as below.

- **H0 :** βi = 0 for all i which means panel data has unit root test.
- **HA :** βi < 0 for at least one cross-section which means panel data has no unit root. Two alternatives are specified and tested a unit root with an intercept and as unit root with trend and intercept. The test statistics can be written as follows.

$$Z_{tbar} = \frac{\sqrt{n}(tbar_{NT} - N^{-1}\sum_{t=1}^{N} E(t_{Ti})}{\sqrt{N^{-1}\sum_{t=1}^{N} Var(t_{Ti})}}$$

Where tbarNT is the average ADF t- statistics

E(tTi)and V ar(tTi) are mean and the variance and computed based on Monte-Carlo simulated moments. They depend on the time dimension, lag order and structure of ADF test. IPS test is one –sided lower tail test approached to standard normal distribution. Only balanced panel data is applicable according to the theory but in reality, when unbalanced data is applied, more simulations are required to get critical values.

Fisher Type Test (Maddala and Wu 1999)

Test statistics discussed by Maddala and Wu are based on Fisher (1932) and combining p-values of t statistics for each unit root of each cross' section [15]. Fisher tests do not need to use the same unit root test in each cross section. This test permits different first-order autoregressive coefficients and tests stationary of null hypothesis and is similar to IPS. The Fisher test statistics is written as below:

$$P(\lambda) = -2\sum_{t=1}^{N} ln(P_i)$$

Where P (λ) is Fishers panel unit root test, all N cross section. Pi is P-value of ADF test for cross-section i and the test follows chi - square distribution with 2N degree of freedom. Fisher test is more flexible, accurate and powerful than LLC test and also has an advantage over IPS. This test allows panel unit root test with no intercept or trend. Maddala and Wu stated that "Fisher test is simple, straight forward and better test than LL and IPS [15]. Inverse normal test (Z) equation and logit test is.

$$Z = -\frac{1}{\sqrt{N}}\sum_{t=1}^{N} \Phi^{-1}(P_i)$$

$\Phi-1$ is he inverse of standard normal cumulative distribution function

The null and alternative hypotheses are as below
- **H0 :** Pi = 1 , which means panel data has unit root.
- **HA :** Pi < 1 , which means panel data do not have unit root.

Panel ARDL Approach
Upon performing unit root and a cointegration tests, the panel ARDL model will be computed. The ARDL model differentiates between short- and long-run coefficients and can be employed reliably throughout short sample periods. Pesaran and Shin found that even with a small sample size, the long-run variables are super-consistent, and the short-run parameters are consistent [18].

Thus, equation (1) is transformed into a panel ARDL (p,q1,q2,q3,q4,q5,q6,q7) equation, with p representing the lags of the dependent variable and q representing the lags of the independent variables. The panel ARDL estimation tests use pooled mean group (PMG) estimation methods. The PMG predictor is capable of estimating links in short runs, incorporating parameters. The basic model is formed as follows:

$$(UNE)_{it} = \delta + \alpha_1(GDPg)_{i,t-1} + \alpha_2(LFg)_{i,t-1} + \alpha_3(FDI)_{i,t-1} + \alpha_4(GFCf)_{i,t-1} + \alpha_5(EX)_{i,t-1} + \alpha_6(IM)_{i,t-1} + \alpha$$

This equation shows that the PMG estimator with a high order of lag can estimate long-run average parameters consistently. The long-run relationship model using the PMG estimators are as follows:

$$(UNE)_{it} = \alpha_i + \sum_{p} \lambda_{ij}(UNE)_{i,t-j} + \sum_{q1} \delta_{1ij}(GDPg)_{i,t-j} + \sum_{q2} \delta_{2ij}(LFg)_{i,t-j} + ... + \sum_{q7} \delta_{7ij}(INF)_{i,t-j} + \epsilon_{it}$$

Where, i represents the number of countries (5), t is the number of years (1991-2023), (p,q1,q2,q3,q4,q5,q6,q7) is the optimum time lag, αi is the countries specific effect, and ϵit refer to the remainder error terms. The short-run relationship with an error correction model is as follows:

$$\Delta(UNE)_{it} = \alpha_i + \Phi_i((UNE)_{i,t-1} - \lambda_1(GDPg)_{it-1} - \lambda_2(LFg)_{it-1} - ... - \lambda_5(INF)_{it-1}) + \sum_p \lambda_{ij}\Delta(UNE)_{i,t-j} + \sum_{q2} \delta_{2ij}\Delta(LFg)_{i,t-j} + ... + \sum_{q7} \delta_{7ij}\Delta(INF)_{i,t-j} + \epsilon_{it}$$

While λi are long-run variables, and Φi is the variable for the error-correction term, which represents the pace of correction to the long-term equilibrium of UNE due to shifts in GDPg, LFg, .., and (INF . Φi implies the presence of a long-term relationship. The negative and substantial value of Φi implies a co-integrating connection between GDPg, LFg, .., and INF .

Empirical Results

Panel Unit Root Test
We can see that all three tests show insignificant results for all variables at the level, which means that the null hypothesis is accepted for all, concluding that all the variables are 1(1). This is the major reason that is making pooled OLS and fixed effect models spurious. Hence, in the presence of nonstationary variables, a co-integration test is required, which provides evidence that these variables are related in the long run or not.

Table 1: Unit root tests

Variables	LLC	IPS	MW	Prob.	Order of integration
UNE	-4.40831	-5.82977	67.3017	0.0000	1st difference
GDPg	-2.79368	-3.35528	40.2705	0.0000	At level
LFg	-4.98157	-5.46487	63.7455	0.0000	1st difference
FDI	-7.03019	-9.34794	110.657	0.0000	At level
GFcf	50.2289	-8.52297	80.9759	0.0000	1st difference
EX	-2.18092	-1.97538	26.7465	0.0026	At level
IM	5.2289	-8.52297	8.9759	0.0000	1st difference
INF	-2.18092	-1.97538	26.7465	0.0026	At level

Based on unit root test I(1) or first different, there are 7 statistics in this majority (LLC, IPS and MW) are significant, showing that the selected variables are cointegrated with each other (Table 1). Based on this test, which is significant, it shows that these variables are integrated as their residuals show convergence. Hence, we can estimate the long-run coefficients.

Short Run Model
Table 2: PMG Short Run Model and ECM

Variables	Coefficient	Std. Error	t-Statistic	Prob.
ECT	-.1564097	.0656284	-2.38	0.017
GDP D1.	- .0935977	.0415811	2.25	0.024
FDI D1.	-.2499802	.282981	-0.88	0.377
LFP D1.	-.1466583	.0684473	-2.14	0.032
GFC D1.	-.0110707	.0082374	-1.34	0.179
Cons	-2.410388	1.05849	-2.28	0.023

The ECT calculates the speed of adjustment of the dependent variable (unemployment rate) towards its long-run equilibrium path. A negative ECT suggests that the system corrects deviations from the long-run equilibrium. The coefficient for ECT is -.1564097. This implies that, on average, the unemployment rate adjusts by approximately - 0.16 units towards its long-run equilibrium for each unit deviation from the equilibrium path in the previous period. A negative sign is expected, indicating that the system corrects disequilibrium over time. The coefficient for the first difference of inflation rate (gdp D1) is - -0.0935977, and this implies that a one-unit increase in the first difference of GDP is associated with a decrease of approximately 0.10% in the unemployment rate of North African nations.

The coefficient for the first difference of the foreign direct investment (fdi D1) is -.2499802. The coefficient for the first difference of the labor force growth (lfp D1) is -.1466583. This suggests that a one-unit increase in the first difference of the interest rate results in an increase of approximately 0.17% in the unemployment rate of North Africa. The coefficient for the first difference of the gross fixed capital formation (gfc D1) is -.0110707. This implies that a one-unit increase in the first difference of the unemployment rate is associated with an increase of approximately 0.11% in the unemployment rate of North African countries.

Long Run Model

Table 3: PMG Long Run Model

Variables	Coefficient	Std. Error	t-Statistic	Prob.
GDP	-1.4220	.3096813	-4.59	0.000
FDI	.016019	.2022246	0.08	0.937
LFP	.650251	.163726	3.97	0.000
GFC	.059739	.0475183	1.26	0.209

The coefficient for gross domestic product growth is -1.4220. This suggests that holding other variables constant, a one-unit increase in gross domestic product growth is associated with a decrease of approximately 0.14 % in the unemployment rate of North African countries. The coefficient for foreign direct investment is .016019 , t-statistic of 0.08 and p-value of 0.937. The coefficient for labor force growth is 0.650251, with t-statistic value of 3.97 and p-value of 0.000. The coefficient of gross fixed capital formation is 0.059739, with t-static of 1.26 and the p-value of 0.209. This infers that holding other variables constant, a one-unit increase in the gross fixed capital formation resulted in an increase of approximately 0.05% in the unemployment rate of North African countries.

Conclusion

The study utilized the panel ARDL model in determining the influence of macroeconomic indicators on the unemployment rate of North African countries. The study found a long-term correlation between a decline in the unemployment rate and growth in the gross domestic product. This finding contradicted that of Rahman, M. S. and is consistent with that of Lozanoska and Dzambaska and Makun and Azu, who found a significant negative relationship between the unemployment rate and GDP growth [19, 20, 9]. The study also showed that the unemployment rate in North African nations is significantly and negatively impacted by exchange. The results contradict those of Nagel and are consistent with those of Ahmed et al. [21, 22].

The study also found that the unemployment rate in North African countries is negatively and statistically significantly impacted by labor force growth. This means that a rise in labor force growth causes the unemployment rate in North African countries to drop by about 0.90 units. The finding is congruent with those of Soylu et al. [23]. A negative ECT suggests that the system corrects deviations from the long-run equilibrium. The coefficient for ECT is - 0.1584123. This means that for every unit deviation from the equilibrium path in the preceding period, the unemployment rate, on average, moves closer to its long- term equilibrium by about - 0.16 units. The system corrects disequilibrium over time, as indicated by the expected negative sign [24-30].

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