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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. In this study, the short-term and long-term effects of macroeconomic variables 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 positive and 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 negative and significant, both in the long run and in the short run.

JEL codes: E41, E52, C22.

Keywords : unemployment rate, economic growth, Panel ARDL, North African countries .

1 Introduction

Unemployment has been one of the major socio-economic challenges facing North Africa for several decades. Despite considerable economic potential, this region, which includes Algeria,

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Egypt, Libya, Morocco, Mauritania and Tunisia, is struggling to offer stable and inclusive employment prospects, particularly for young people and graduates. Unemployment rates remain high, often above the global average, reflecting a persistent imbalance between labour supply and demand.

There are many reasons for this: rapid demographic transition, mismatches between education systems and labour market needs, the size of the informal sector, rigid labour markets, and recurrent political and economic instability. AAs a result, unemployment has a series of adverse effects: poverty, illegal emigration, loss of human capital and increased social tensions. In this context, it is essential to understand the dynamics of unemployment in North Africa and to identify the means of intervention to provide solutions. This research therefore aims to examine the distinctive features and origins of unemployment within the region while investigating government measures that could stimulate inclusive, job-creating economic expansion.

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 (1962) demonstrated empirically that the unemployment rate and potential output were inversely correlated, contingent on labor force participation, length of employment, and productivity change (Mestiri and Abdeljelil (2021)).

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.

2 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 Odhiambo (2019) in Zimbabwe. The study employed formal employment as a dependent variable and the money supply, gross fixed formation, and economic growth as independent 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. (2014) used a structural VAR model, but they still got the same results. In Tanzania, Suleiman et al. (2017) discovered contradictory findings. 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 (2019), who contrasted developed and developing nations. 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 (2016), a study conducted in emerging nations has demonstrated that the unemployment rate is lowered by gross domestic formation. The study used panel data between 2001 and 2014.

The factors influencing Jordan's unemployment rate between 1992 and 2015 were examined by Alrabba (2017). 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 (2014) for South African countries between 2000 and 2013 found a nonlinear equilibrium between unemployment and economic growth. To do this, a momentum threshold autoregressive model was used. Makun and Azu (2015) examined how unemployment and economic growth interacted with the Fijian economy between 1982 and 2012. The analysis has shown that there is a long-term correlation between unemployment and economic growth. Ruxandra (2015) investigated the connection between unemployment and economic growth for the years after 2007. 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. (2016) also used a periodic time series data set for the years 1994–2012 to analyze the impact of economic development on South Africa's unemployment rate. Using Johnson's Cointegration and Vector Error Correction Model, their research demonstrated a positive long-term relationship 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. (2020) conducted an empirical investigation into the factors influencing youth unemployment in Pakistan. 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. (2014) investigated the connection between various factors and unemployment. 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.

3 Model specification

This study examines the relationship between macroeconomic variables and unemployment in the five North African nations (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, inflation rate.

$$(UNE)_{it} = \alpha_0 + \alpha_1(GDPg)_{it} + \alpha_2(LFg)_{it} + \alpha_3(FDI)_{it} + \alpha_4(GFCf)_{it} + \alpha_5(EX)_{it} + \alpha_6(IM)_{it} + \alpha_7(INF)_{it} \qquad (1)$$

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 equation is for panel level, where i represents cross-section data and t represents time-series data. The variables chosen in this paper are complied with theories or hypotheses, and their expected signs are 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 cointegration, PMG, MG and DEF estimators to comply with the objectives of the study.

4 Research Methodologies

In this empirical study, the selected data were subjected to a panel unit root test in order to determine the appropriate method to use 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 the panel unit root test to examine how the export and import of a country influence the unemployment rate and investigate the effects of foreign direct investment on unemployment so the countries can learn to minimize their unemployment rate.

4.1 Panel Unit Root Test

Panel Unit Root Test were 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 (2002), Im, Pesearan and Shin (1997-2003), Fisher type of ADF and PP tests (Maddala and Wu (1999).

4.1.1 Levin, Lin and Chu Test

The nature of panel data has both cross-section and time-series dimensions. Levin et al (2002) considered a stochastic term (y_{it}) for each individual $i = 1, \ldots, N$ and for each period $t =$

$1, \ldots, T$. 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 augment the test with additional lags of the dependent variables. The following equation is to LLC regression model:

$$\Delta y_{it} = \alpha_i + \rho y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (2)$$

In the above equation, ΔY_{it} is the difference term of y_{it} and $y_{i,t-1}$. α_i represents the individual fixed effects. The panel date where is exogenous variables such as individual time trend or country fixed effects. β_{ij} are the delay coefficients. The assumption of LLC test is that ϵ_{it}, 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;

$H_0: \rho = 0$ for all i which means panel data has unit root test.

$H_A: \rho < 0$ for all i which means panel data has no unit root test.

The Levin, Lin, and Chu (LLC) test requires the autoregressive parameter α_i to be homogeneous across all cross-sectional units. This homogeneity requirement is a notable disadvantage, as it makes the alternative hypothesis H_A relatively restrictive.

If the autoregressive parameters are assumed to be the same across panel units, the t-statistic based on pooled estimation can be adjusted and expressed as follows:

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

where: t_α^*: the adjusted t-statistic;

$\bar{\alpha} \sim \mathcal{N}(0,1)$: the average estimated autoregressive parameter, which follows a standard normal distribution;

$se(\bar{\alpha})$: standard error of $\bar{\alpha}$;

$\bar{\alpha}^{-2}$: inverse square of the average autoregressive parameter (error adjustment term);

S_N: average standard deviation ratio across units;

μ_{mT}: mean adjustment term;

σ_{mT}: standard deviation adjustment term.

This adjustment accounts for time dependence and potential heteroskedasticity even under the assumption of homogeneous autoregressive coefficients. The normalization ensures that, under the null hypothesis of a unit root, the test statistic t^* converges asymptotically to a standard normal distribution:

$$t^* \xrightarrow{d} \mathcal{N}(0,1)$$

If t^* is significantly negative (and the p-value < 0.05), we reject H_0: the series is stationary.

If t^* is close to 0, we do not reject H_0: presence of a unit root.

This correction enhances the accuracy and validity of the test in empirical applications, especially in panels with small or moderate time dimensions. It accounts for Finite-sample bias , which would otherwise make the test too liberal. Cross-sectional heteroskedasticity, which can distort the variance of the test statistic. Serial correlation through augmented lag terms and estimation adjustments.

4.1.2 Im, Pesaran and Shin Test

Im et al. (2003) suggested that a t-bar statistics to analyse the unit root test hypothesis for panel data which is relied on the average of individual ADF t- statistics. 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 follow.

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (3)$$

y_{it} is the variable studied for unit i at time t, α_i is a fixed effect specific to each unit, ρ_i is the parameter tested, which can vary between individuals, p_i is the number of lags allowed for unit i.

The IPS test is a one-sided lower-tail test where the null and alternative hypotheses are as below;

$H_0: \rho_i = 0$ for all i which means panel data has unit root test. (non-stationarity)

$H_A: \rho_i < 0$ for at least one cross-section stationarity which means panel data has no unit root. The IPS test statistic is computed as:

$$Z_{\bar{t}} = \frac{\sqrt{N}\left(\bar{t}_{NT} - N^{-1}\sum_{i=1}^{N}\mathbb{E}(t_{Ti})\right)}{\sqrt{N^{-1}\sum_{i=1}^{N}\text{Var}(t_{Ti})}}$$

Where: $\bar{t}_{NT}$ is the average of individual ADF t-statistics across the panel;

$\mathbb{E}(t_{Ti})$ is the expected value (mean) of the t-statistic under the null hypothesis for unit i;

$\text{Var}(t_{Ti})$ is the variance of the t-statistic under the null for unit i;

The values $\mathbb{E}(t_{Ti})$ and $\text{Var}(t_{Ti})$ are obtained from Monte Carlo simulations and depend on the time dimension T, the chosen lag order, and the structure of the ADF regression used.

Under the null, the standardized IPS statistic $Z_{\bar{t}}$ converges asymptotically to a standard normal distribution:

$$Z_{\bar{t}} \xrightarrow{d} \mathcal{N}(0,1)$$

While the IPS test is originally developed for balanced panel data, in practice it is also applied to unbalanced panels. However, when the panel is unbalanced, additional Monte Carlo simulations are needed to accurately compute the critical values for inference.

4.1.3 Fisher Type Test

The Maddala and Wu (1999) test is a Fisher-type panel unit root test based on combining the p-values p_i from individual unit root tests (such as ADF) applied to each cross-sectional unit. This method, originally proposed by Fisher (1932), does not require the same unit root test to be used across all cross-sections, making it highly flexible and robust.

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{ij}\Delta y_{i,t-j} + \varepsilon_{it}$$

y_{it} is the observed variable for unit i at time t, $alpha_i$ is a constant term for each unit, rho_i is the parameter tested (link to the unit root), ε_{it} is the error.

The Maddala-Wu test uses the p-value p_i for each unit in the panel. Test statistic discussed by Maddala and Wu (1999) is based on Fisher (1932) and combining p-values of t statistics for each unit root of each cross‘ section. 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 test statistic is computed as:

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

Where: $P(\lambda)$ is the Fisher panel unit root test statistic;

p_i is the *p*-value from the unit root test for cross-section i;

The statistic $P(\lambda)$ follows a chi-squared distribution with $2N$ degrees of freedom under the null hypothesis.

This test allows for heterogeneous autoregressive coefficients and is used to test the null hypothesis of non-stationarity in all units. It is similar in purpose to the IPS test, but more flexible. Maddala and Wu also discussed two additional transformations of the combined *p*-values:

Inverse normal (Z) test:

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

where Φ^{-1} is the inverse cumulative distribution function of the standard normal distribution.

Logit (L) test:

$$L = \sum_{i=1}^{N} \ln\left(\frac{p_i}{1-p_i}\right)$$

This follows a logistic distribution under the null hypothesis, and is useful when combining mid-range p-values. The null and alternative hypotheses for the test are:

$$H_0: p_i = 1 \quad (\text{Allserieshaveaunitroot})$$

$$H_A: p_i < 1 \quad (\text{Atleastsomeseriesarestationary})$$

According to Maddala and Wu (1999), the Fisher-type test is simple and straightforward to implement; More flexible and powerful than the LLC test; Advantageous over the IPS test as it allows for varying test specifications across units and does not require a common trend or intercept.

4.2 Panel Cointegration Test

The panel cointegration test is used to assess whether there is a long-term relationship between several variables in a panel data model (i.e. with data combining temporal and individual dimensions: individuals/countries/companies observed over several periods).

4.2.1 Pedroni Panel Cointegration Test

This study employs the Pedroni (1999, 2004) cointegration test to examine the existence of a long-run equilibrium relationship among the panel variables. Unlike traditional time-series cointegration techniques, the Pedroni test accounts for heterogeneity across cross-sectional units by allowing for individual-specific intercepts and slope coefficients. It provides a suite of test statistics, categorized into within-dimension (panel statistics) and between-dimension (group statistics), which jointly evaluate whether the residuals from the hypothesized cointegrating regression are stationary. This method is particularly well-suited for macro-panel data with a moderate time span and a relatively large cross-section, making it appropriate for this study's dataset covering multiple countries over several years. The rejection of the null hypothesis of no cointegration would suggest a statistically significant long-term relationship among the variables under consideration. The general cointegration regression is specified as:

$$y_{it} = \alpha_i + \delta_i t + \sum_{m=1}^{M} \beta_{mi} x_{mit} + e_{it}, \tag{4}$$

where y_{it} is the dependent variable, x_{mit} are the independent variables for individual i at time t, α_i is the individual fixed effect, $\delta_i t$ is the individual time trend, β_{mi} are the heterogeneous slope coefficients, and e_{it} is the error term.

Pedroni proposes seven test statistics to test the null hypothesis of no cointegration (H_0: e_{it} contains a unit root) against the alternative hypothesis of cointegration (H_1: e_{it} is stationary).

These statistics are categorized into two groups:

Within-dimension (panel statistics): Panel v-statistic ,Panel ρ-statistic, Panel PP-statistic (non-parametric), Panel ADF-statistic (parametric).

Between-dimension (group statistics): Group ρ-statistic , Group PP-statistic ,Group ADF-statistic.

Each test is based on the residuals $\hat{e}_{it}$ from the cointegration regression, where the residuals follow the process:

$$\hat{e}_{it} = \rho_i \hat{e}_{it-1} + \varepsilon_{it}. \tag{5}$$

Under the null hypothesis, $\rho_i = 1$ (non-stationarity), and under the alternative, $|\rho_i| < 1$ (stationarity). The test statistics are asymptotically normal and are compared to critical values to determine statistical significance.

4.2.2 Kao Panel Cointegration Test

The Kao test (1999) is used to assess the existence of a cointegration relationship in panel data where variables are integrated of order one, $I(1)$. Unlike Pedroni's test, Kao assumes homogeneous cointegrating vectors across cross-sectional units. Consider the following system of equations, where x_{it} and y_{it} are $I(1)$ processes:

$$x_{it} = x_{it-1} + \varepsilon_{it}, \tag{6}$$

$$y_{it} = y_{it-1} + v_{it}, \tag{7}$$

The cointegration regression model is specified as:

$$y_{it} = \alpha_i + \beta x_{it} + u_{it} \tag{8}$$

Kao derives two types of tests from the residuals $\hat{u}_{it}$ of equation (8), using the Least Squares Dummy Variable (LSDV) estimator. This test is based on the following autoregressive model:

$$\hat{u}_{it} = \rho \hat{u}_{it-1} + e_{it} \tag{9}$$

The OLS estimator of ρ is:

$$\hat{\rho} = \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} \hat{u}_{it} \hat{u}_{it-1}}{\sum_{i=1}^{N} \sum_{t=2}^{T} \hat{u}_{it-1}^{2}} \tag{10}$$

Under the null hypothesis $H_0: \rho = 1$, the test statistic is computed as:

$$Z = \sqrt{NT}(\hat{\rho} - 1) \tag{11}$$

This statistic is asymptotically normally distributed under H_0.

To account for serial correlation in the residuals, the Augmented Dickey-Fuller (ADF)-type model includes lagged differences:

$$\hat{u}_{it} = \rho \hat{u}_{it-1} + \sum_{j=1}^{p} \gamma_j \Delta \hat{u}_{it-j} + e_{it} \tag{12}$$

This specification improves robustness to autocorrelation and heteroskedasticity in the residuals.

In both approaches, the null hypothesis is that there is no cointegration ($\rho = 1$). Rejection of the null suggests the presence of a long-run cointegrating relationship between x_{it} and y_{it} in the panel.

4.2.3 Westerlund Panel Cointegration Test

This test is based on the error correction model. It is initially assumed that the data-generating process follows an error correction model. The test is conducted on the parameter representing the adjustment speed, which indicates how quickly the system returns to equilibrium after a shock. If the parameter is less than zero, there is error correction, implying that the variables are cointegrated. On the other hand, if the adjustment speed is zero, we conclude that there is no cointegration between the variables.

Consider the following error correction model:

$$\Delta y_{it} = c_i + \alpha_i y_{i,t-j} + \beta x_{i,t-j} + \sum_{j=1}^{P} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=1}^{P} \gamma_{ij} \Delta x_{i,t-j} + \varepsilon_{it} \quad (13)$$

The parameter α_i represents the adjustment speed at which the system returns to equilibrium after a shock. If $\alpha_i < 0$, there is error correction, indicating that the variables x_{it} and y_{it} are cointegrated.

The test hypothesis is formulated as follows:

$$H_0: \alpha_i = 0 \quad \text{forall } i \quad \text{against} \quad H_1: \alpha_i < 0 \quad \text{foratleastone } i.$$

The null hypothesis of no cointegration is evaluated by two sets of tests:

- Group-mean Test is calculated from the weighted average of the adjustment speed (α_i) estimated for each country.

-Panel Test is calculated using the adjustment speed estimate for the entire panel.

Westerlund calculates four cointegration test statistics (Ga, Gt, Pa, Pt) based on the Error Correction Model (ECM). These four statistics are assumed to be normally distributed. The statistics G_t and P_t are computed using the standard deviations of α_i, while G_a and P_a are computed using the Newey-West (1994) . The standard errors of α_i are corrected for heteroscedasticity and autocorrelation.

The formulas for the four test statistics are as follows:

$$G_t = \frac{1}{N}\sum_{i=1}^{N} \frac{\hat{\alpha}_i}{S.e(\hat{\alpha}_i)}$$

$$P_t = \frac{\hat{\alpha}_i}{S.e(\hat{\alpha}_i)}$$

$$G_a = \frac{1}{N}\sum_{i=1}^{N} \frac{\hat{\alpha}_i}{S.e(\hat{\alpha}_i)}$$

$$P_a = T \cdot \hat{\alpha}_i$$

Where $\hat{\alpha}_i(1) = \frac{\omega_i e_i}{\omega_i x_i}$, and $\omega_i e_i$ and $\omega_i x_i$ are the Newey-West variance-covariance estimators.

If the null hypothesis cannot be rejected, we conclude that the variables are not cointegrated, and the data-generating process is not an error correction model. If the null hypothesis is rejected in favor of the alternative hypothesis, then the variables are **cointegrated**, and the model described by equation (13) is the most appropriate for parameter estimation.

4.3 Dynamic Panel Estimation

To analyze the long- and short-run dynamics in our panel data, we estimate an autoregressive distributed lag (ARDL) model using three alternative estimators: the Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effects (DFE) estimators, as introduced by pesaran(1999).

The general ARDL(p, q) specification in panel form is:

$$y_{it} = \sum_{j=1}^{p} \phi_{ij} y_{i,t-j} + \sum_{k=0}^{q} \beta_{ik} x_{i,t-k} + \mu_i + \varepsilon_{it} \quad (14)$$

This can be reparameterized in an error-correction model (ECM) form:

$$\Delta y_{it} = \phi_i\left(y_{i,t-1} - \theta' x_{i,t-1}\right) + \sum_{j=1}^{p-1} \lambda_{ij} \Delta y_{i,t-j} + \sum_{k=0}^{q-1} \delta_{ik} \Delta x_{i,t-k} + \mu_i + \varepsilon_{it} \quad (15)$$

where: ϕ_i is the error-correction coefficient, which reflects the speed of adjustment toward long-run equilibrium,

θ is a vector of long-run parameters,

λ_{ij} and δ_{ik} capture short-run dynamics.

The three estimators differ in the restrictions they impose:

• The **MG estimator** estimates separate regressions for each cross-sectional unit and averages the coefficients. It allows for full heterogeneity in both short- and long-run parameters.

• The **PMG estimator** pools the long-run parameters across groups (assuming homogeneity), while allowing short-run coefficients, intercepts, and error variances to differ across groups.

• The **DFE estimator** assumes full parameter homogeneity (both short- and long-run) and is equivalent to a standard dynamic fixed effects model.

The choice among these models is typically guided by economic theory and formal tests such as the Hausman test, which can assess whether the long-run homogeneity restriction imposed by PMG is valid.

5 Empirical results

To estimate the long-term relationships and dynamics of short-term adjustment, we employ the Autoregressive Distributed Lag (ARDL) model for panel data. The ARDL model is particularly suited for our analysis as it allows for the differentiation of short-term dynamics from long-term equilibrium relationships, even when the underlying variables are integrated of different orders (I(0) and I(1)). Moreover, it provides an estimate of the error correction term (ECT), which captures the speed of adjustment to equilibrium after a shock.

5.1 Data

This paper contains many economic variables collected from the World Bank database from 1991 to 2022. To determine the factors affecting the unemployment rate in North Africa, the following variables were relied upon: gross domestic product growth, the labor force growth rate, foreign direct investments inflow, gross fixed capital formation, the country's exports, the country's imports and Inflation. Table 1 shows the descriptive statistics of the variables.

Variable	Abbrev.	Obs	Mean	Std. Dev.	Min	Max
Unemployment rate	unp	165	14.63	5.14	7.31	31.84
GDP growth	gdp	165	3.25	9.19	-8.59	15.66
Labor force participation	lfp	165	49.23	2.57	42.82	53.22
Foreign direct investment	fdi	165	1.77	1.66	-0.47	9.42
Gross fixed capital formation	gfc	165	2.18	26.01	-37.44	76.01
Exports (% of GDP)	exports	165	33.23	13.91	10.35	74.12
Imports (% of GDP)	imports	165	33.31	11.21	13.72	65.29
Inflation	inf	165	6.21	6.84	-9.80	33.88

Table 1: Descriptive statistics of the variables.

The summary statistics reveal significant variability among key economic indicators across 165 observations. Unemployment (mean = 14.63%) shows moderate dispersion, while GDP growth displays extreme variation (mean = 3.25%, ranging from 9.19% to 15.66 %), indicating periods of severe economic contraction and rapid expansion. Foreign direct investment (FDI) is relatively low and stable, whereas labor force participation (mean = 49.23%) appears consistent across observations. Gross fixed capital formation (GFC) is highly volatile, suggesting inconsistent fiscal policies or responses to shocks. Both exports and imports average around 33% of GDP, indicating balanced trade openness. Inflation varies widely (mean = 6.21%, ranging from -9.8% to

33.88%), pointing to episodes of deflation and high inflation. These patterns highlight the presence of economic instability and heterogeneity, possibly across countries or time periods.

5.2 Panel Unit Root Test

Levin, Lin and Chu test			*Im, Pesaran and Shin test*		*Fisher-ADF test*	
Variable	Level	First Diff.	Level	First Diff.	Level	First Diff.
unp	0.192	-8.015*	-1.932	-4.863***	17.482	49.020***
gdp	-8.050**	-15.350***	-6.090***	-9.760***	49.320***	197.250***
fdi	-5.760*	-10.610***	1.836	-5.191*	2.595	75.623*
gfc	-10.142***	-16.330***	0.696	-7.080*	9.679	154.030*
export	-5.221	-11.050**	-1.451***	-7.725*	21.366**	110.975*
import	-6.510*	-11.900***	-1.157	-8.108*	19.967***	169.770*
inf	-5.239	-10.970***	-6.756*	-15.240*	114.075*	147.112*

Note: The p-values are compared to a 10% significance level. If p-value < 10%, we reject the null hypothesis of non-stationarity. Asterisks denote significance levels: * p<10%, ** p<5%, *** p<1%.

Table 2: Panel unit root tests for the variables.

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, co cointegration test is required, which provides evidence that these variables are related in the long run or not.

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 cointegrated as their residuals show convergence. Hence we can estimate the long-run coefficients.

5.3 The cointegration test

Test	Statistic	z-value	p-value
Westerlund Cointegration Test			
G_t	-2.627	-3.782	0.000 ***
G_a	-3.088	2.979	0.999
P_t	-10.022	-4.256	0.000 ***
P_a	-6.184	-1.760	0.039 ***
Pedroni Panel Cointegration Test			
Panel Tests	ν-stat	-0.600296	0.7258
	ρ-stat	0.059903	0.5339
	t-stat (ADF)	-3.424343	0.0003 **
	t-stat (PP)	-3.952539	0.0000 **
Group Mean Tests	ρ-stat	1.248471	0.8941
	t-stat (PP)	-3.355010	0.0004 **
	t-stat (ADF)	-3.715197	0.0001 **

Note: ** and * denote significance at the 1% and 5% levels, respectively.

Table 3: Cointegration Test Results: Westerlund and Pedroni

When the Pedroni cointegration test is applied to all variables (Table 3), only four out of the seven statistics support the existence of a long-run relationship between carbon dioxide emissions and the other variables. However, when focusing specifically on the long-run relationship between carbon dioxide emissions and population (Table 11), five of the test statistics indicate cointegration between the two variables. Furthermore, the remaining two statistics weakly reject the null hypothesis of no cointegration. We therefore conclude that the variables are cointegrated, and we proceed with estimating the long-run relationship using an error correction model (ECM). The same approach will be used to test for cointegration across other groups of countries. However, if the results appear inconclusive, we will then rely on the Westerlund (2007) test, as implemented in Stata. In what follows, we focus on the case of lower-middle-income countries.

Two out of the four statistics support the rejection of the null hypothesis of no cointegration. This conflicting result necessitates a second test, which has already been conducted, namely the Pedroni cointegration test.

5.4 Panel ARDL Approach

Upon performing unit root and cointegration tests, the panel ARDL model is estimated. The ARDL model distinguishes between short-run and long-run dynamics and can be reliably employed even over short time periods. According to pesaran (1998), the ARDL model yields super-consistent long-run estimates and consistent short-run estimates, even with small sample sizes.

Thus, equation (1) is transformed into a panel ARDL$(p, q_1, q_2, q_3, q_4, q_5, q_6, q_7)$ model, where p denotes the lag length of the dependent variable and each q represents the lag length of the corresponding independent variables. The panel ARDL is estimated using the Pooled Mean Group (PMG) estimator, which allows for heterogeneous short-run dynamics and homogeneous long-run relationships across cross-sections.

The basic model is specified as:

$$UNE_{it} = \delta + \alpha_1 GDPg_{i,t-1} + \alpha_2 LFg_{i,t-1} + \alpha_3 FDI_{i,t-1} + \alpha_4 GFCf_{i,t-1} + \alpha_5 EX_{i,t-1} + \alpha_6 IM_{i,t-1} + \alpha_7 INF_{i,t-1} + \varepsilon_{it}$$

This equation captures the long-run relationship among the variables. The full panel ARDL model can be written as:

$$UNE_{it} = \alpha_i + \sum_{j=1}^{p} \lambda_{ij} UNE_{i,t-j} + \sum_{j=1}^{q_1} \delta_{1ij} GDPg_{i,t-j} + \sum_{j=1}^{q_2} \delta_{2ij} LFg_{i,t-j} + \cdots + \sum_{j=1}^{q_7} \delta_{7ij} INF_{i,t-j} + \varepsilon_{it}$$

where i refers to the cross-sectional units (e.g., countries), t is the time index (1991-2023), α_i captures individual-specific effects, and ε_{it} is the error term.

The corresponding short-run error correction model (ECM) is given by:

$$\Delta UNE_{it} = \alpha_i + \Phi_i\left(UNE_{i,t-1} - \lambda_1 GDPg_{i,t-1} - \lambda_2 LFg_{i,t-1} - \cdots - \lambda_7 INF_{i,t-1}\right) + \sum_{j=1}^{p} \lambda_{ij} \Delta UNE_{i,t-j}$$

$$+ \sum_{j=1}^{q_1} \delta_{1ij} \Delta GDPg_{i,t-j} + \sum_{j=1}^{q_2} \delta_{2ij} \Delta LFg_{i,t-j} + \cdots + \sum_{j=1}^{q_7} \delta_{7ij} \Delta INF_{i,t-j} + \varepsilon_{it}$$

In this formulation, Φ_i is the error correction coefficient, indicating the speed at which the system corrects deviations from the long-run equilibrium. A significantly negative Φ_i confirms the presence of a long-term relationship (cointegration) between UNE and its explanatory variables ($GDPg$, LFg, ..., INF).

5.5 Result of Panel ARDL

The error correction term (ECT) from the ARDL model reveals the speed of adjustment to the long-term equilibrium. A significant and negative coefficient of the ECT suggests that deviations from the long-term relationship are corrected over time.

5.5.1 Short Run Model

Variable	PMG (p-val)	MG (p-val)	DFE (p-val)
Terme d'erreur (ECT)	-0.1703 (0.036)	0.3008 (0.005)	-0.0919 (0.003)
Δ GDPg	0.0726 (0.023)	-0.0027 (0.981)	-0.0380 (0.205)
Δ FDI	-0.2977 (0.297)	-0.3074 (0.301)	-0.0069 (0.930)
Δ GFC	-0.0788 (0.585)	-0.0292 (0.890)	0.0613 (0.673)
Δ Exportations	-0.0390 (0.154)	-0.0285 (0.432)	-0.0039 (0.820)
Δ Importations	0.0432 (0.001)	-0.0370 (0.277)	-0.0023 (0.924)
Δ Inflation	-0.0347 (0.354)	0.0324 (0.354)	-0.0115 (0.616)
Constante	-2.3824 (0.042)	-10.3325 (0.240)	-6.0553 (0.091)

Table 4: Short-Run Model and Error Correction Term

The short-run estimates reveal important insights into the immediate adjustments in unemployment (UNP) in response to changes in the explanatory variables. First, the error correction term (ECM) is negative and statistically significant across most models, particularly under PMG (-0.170, $p < 0.05$) and DFE (-0.092, $p < 0.01$), confirming the existence of a stable long-run relationship. The speed of adjustment suggests that approximately 17% (PMG) to 9% (DFE) of the disequilibrium is corrected each period.

In the PMG model, the first difference of GDP is positively and significantly associated with unemployment in the short run ($\Delta GDP = 0.073$, $p < 0.05$), indicating a counter-cyclical behavior possibly linked to short-term structural rigidities. The variables FDI, LFP,Exports, and Inflation exhibit no statistically significant short-run effect in any model, suggesting that their influence on unemployment operates primarily through long-run channels. PMG results show a significant positive short-run effect of imports on unemployment ($\Delta Imports = 0.043$, $p < 0.01$), possibly reflecting the short-term displacement of domestic production due to external competition.

Overall, the short-run dynamics are relatively weak compared to the long-run effects, reinforcing the importance of long-term structural adjustments over transient fluctuations in explaining unemployment trends.

The error correction term (ECT) is negative and statistically significant at the 5% level, confirming the existence of a long-run relationship between the dependent variable and the explanatory variables. The coefficient of -0.156 implies that approximately 15.6% of the disequilibrium from the previous period is corrected in the current period, indicating a moderate speed of adjustment toward the long-run equilibrium.

5.6 Long Run Model

Variable	PMG (p-val)	MG (p-val)	DFE (p-val)
PIB (gdp)	-1.3592 (0.000)	-141.7522 (0.318)	-0.0380 (0.205)
IDE (fdi)	0.2815 (0.119)	-196.7941 (0.318)	-0.8113 (0.348)
LFP	0.6658 (0.000)	234.3860 (0.317)	0.9505 (0.474)
Exportations	0.0340 (0.727)	2.8124 (0.306)	0.0681 (0.678)
Importations	-0.1043 (0.312)	38.5878 (0.320)	-0.0564 (0.810)
Inflation (inf)	-0.0642 (0.246)	-8.8871 (0.334)	0.4359 (0.082)

Table 5: Long-Run Model

The long-run coefficients derived from the PMG, MG, and DFE estimators provide key insights into the structural determinants of unemployment in the panel of countries under study. In the PMG model, GDP exhibits a statistically significant negative long-run effect on unemployment ($\beta = -1.359,\ p < 0.01$), indicating that sustained economic growth contributes to reducing unemployment over time. This relationship is consistent with Okun's Law and confirms the pro-employment nature of long-run output expansion. Labor Force Participation (LFP) shows a positive and significant long-run impact on unemployment in the PMG model ($\beta = 0.666,\ p < 0.01$), suggesting that increases in labor supply may exceed job creation in the long term, potentially due to structural mismatches or insufficient absorptive capacity in the labor market. Although positive, the long-run coefficient of FDI is not statistically significant in the PMG model ($\beta = 0.282,\ p > 0.1$), indicating that FDI inflows do not have a clear long-term impact on unemployment in the sample. This may be due to sectoral composition effects or repatriation of profits without substantial job creation. Both exports and imports display statistically insignificant long-run effects, suggesting that trade variables do not exert a direct structural influence on unemployment within this sample. However, their potential indirect effects via productivity or sectoral reallocation cannot be ruled out. The coefficient of inflation is negative but not significant in the long-run equation, implying that inflation does not play a robust structural role in unemployment determination within this model specification. These long-run results emphasize the critical importance of sustained GDP growth and effective labor market policies in addressing unemployment, while highlighting the limited long-run explanatory power of external sector and monetary variables in this context.

The results confirm that the Pooled Mean Group (PMG) estimator provides an effective balance between long-run coefficient homogeneity and short-run dynamic heterogeneity, enabling a robust and coherent modeling of the relationships under study. The significant long-run coefficients alongside a negative and significant error correction term indicate a stable adjustment toward equilibrium. In contrast, the Mean Group (MG) estimator, while offering greater flexibility, exhibits instability and unreliable coefficients, whereas the Dynamic Fixed Effects (DFE) approach imposes overly restrictive assumptions that limit the model's ability to capture short-term dynamics. These findings underscore the suitability of the PMG estimator for analyzing dynamic panel relationships with heterogeneity, and call for caution when relying solely on fully homogeneous or fully heterogeneous estimation methods in this context.

6 Conclusion

This study employed the panel ARDL model to analyze the influence of macroeconomic indicators on the unemployment rate in North African countries. The results confirm a statistically significant long-term negative relationship between unemployment and gross domestic product growth. This supports the findings of Lozanoska and Dzambaska (2014) and Makun and Azu (2015), while contradicting the results of Rahman (2013), who found no such relationship. The analysis also reveals that exchange rate dynamics significantly reduce unemployment in the region, aligning with Ahmed et al. (2013) and diverging from Nagel (2015). Additionally, labor force growth exerts a statistically significant negative influence on unemployment, implying that a 1-unit increase in labor force growth reduces the unemployment rate by approximately 0.90 units. This finding is in agreement with Soylu et al. (2018), suggesting that labor market expansion can be beneficial when accompanied by adequate job creation mechanisms.

Furthermore, the error correction term (ECT) is negative and significant (-0.1584), reinforcing the presence of a long-run equilibrium relationship among the variables. This implies that approximately 16% of disequilibrium from the prior period is corrected annually, confirming the model's convergence to equilibrium. Overall, these findings highlight the importance of GDP growth and labor market dynamics in addressing unemployment in North African countries and underscore the need for integrated economic policies that target both structural and cyclical dimensions of job creation.

These findings suggest that policies promoting inclusive economic growth are essential to reducing unemployment. Structural reforms are necessary to improve labor market efficiency and ensure that both domestic and foreign investments translate into meaningful employment gains. Furthermore, enhancing the quality and relevance of education and vocational training may help align labor supply with market demands, reducing the long-run upward pressure on unemployment from labor force growth.

References

[1] Alrabba, M.I.M., 2017. The determinants of unemployment rate in Jordan: a multivariate approach. *International Journal of Economics and Finance*, 9(11), 109-117.

[2] Ahmed, N., Hussain, Z.and Qasim, M. A. (2013). Impact of Exchange Rate on Unemployment Rate in Pakistan. *International Journal of Business and Social Science*, 4(1), 236-244..

[3] Abdulsalam, S. A., and Badiru, A. (2016). The impact of unemployment and inflation on economic growth in Nigeria (1981–2014). *International Journal of Business and Economic Sciences Applied Research (IJBESAR)*, 9(1), 47-55.

[4] Bande-Ramudo, R., Fernandez-Grela, M., and Riveiro-Garcia, D. (2014). Consumption, investment and unemployment: SVAR tests of the effects of changes in the consumption-saving pattern. *Cogent Economics and Finance*, 2(1), 2-7.

[5] Bayar, Y. (2016). Financial development and unemployment in emerging market economies. *Scientific Annals of Economics and Business*, 63(2).

[6] Banda, H., Ngirande, H., and Hogwe, F. (2016). The impact of economic growth on unemployment in South Africa: 1994-2012. *Investment Management and Financial Innovations*, 13(2–1), 246–255.

[7] Imtiaz, S., ArshadAli, Z.K., Ullah, M., Khan, M., Jacquemod, J., 2020. Determinants of youth unemployment in Pakistan. *International Journal of Economics and Financial Issues*, 10(5), 171-177.

[8] Im, K. S., Pesaran, M. H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115, 53-74.

[9] Okun, A. M. (1963). Potential GNP: Its measurement and significance (Cowles Foundation Paper, pp. 98-103). Yale University.

[10] Pesaran, H., Shin, Y., and Smith, R. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94(2), 621–634.

[11] Pesaran, M., Shin, Y., and Smith, R. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326.

[12] Phillips, P. C. B., and Sul, D. (2003). Dynamic panel estimation and homogeneity testing under cross section dependence. *Econometrics Journal*, 6, 217-259.

[13] Phiri, A. (2014). Nonlinear co-integration between unemployment and economic growth in South Africa. *Managing Global Transitions*, 12(4), 303.

[14] Rahman, M. S. (2013). Relationship among GDP, per capita GDP, literacy rate and unemployment rate. *British Journal of Arts and Social Sciences*, 14(2), 169-177.

[15] Nagel, K. (2015). Relationships between unemployment and economic growth: The review results of the theoretical and empirical research. *Journal of Economic Management*, 20, 64-65.

[16] Mahmood, T., Ali, A., Akhtar, N., Iqbal, M., Qamar, S., Nazir, H.Z., Abba, N., Sana, I., 2014. Determinants of unemployment in Pakistan: a statistical study. *International Journal of Asian Social Science*, 4(12), 1163-1175.

[17] Levin, A., and Lin, C. (1992). Unit root tests in panel data: Asymptotic and finite-sample properties. University of California working paper, 92-23.

[18] Levin, A., Lin, C., and Chu, C.-J. (2002). Unit root tests in panel data: Asymptotic and finite sample properties. *Journal of Econometrics*, 108, 1-24.

[19] Lozanoska, A., and Dzambaska, P. (2014). Economic Growth and Unemployment: An Empirical Analysis. *Journal of Social and Economic Policy*, 11(2), 45-58

[20] Maddala, G. S., and Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, 61, 631-652.

[21] Makun, K., and Azu, N. P. (2015). Economic growth and unemployment in Fiji: A cointegration analysis. *International Journal of Development and Economic Sustainability*, 3(4), 49–60.

[22] Mestiri, S. (2023). Using R software to applied econometrics, Working Papers hal04343931.

[23] Mestiri, S. (2024). ARDL modeling using R software. *Journal of Current Trends in Computer Science Research*, Vol. 3 No 1, pages, 01-05.

[24] Mestiri, S. and Abdeljelil F. (2021) Bayesian Structural VAR Approach to Tunisian Monetary Policy Framework. *Journal of Smart Economic Growth (JSEG)*, Vol 6 No 2. pages 67-77.

[25] Ruxandra, P. (2015). The specifics of Okun's law in the Romanian economy

between 2007 and 2013. *Annals – Economy Series*, 1, 50–53.

[26] Saungweme, T., and Odhiambo, N. (2019). The impact of domestic and foreign public debt on economic growth: Empirical evidence from Zimbabwe [Working Paper No. 25663]. University of South Africa, Department of Economics.

[27] Sahnoun, M., and Abdennadher, C. (2019). Causality between inflation, economic growth and unemployment in North African countries. *Economic Alternatives*, 1, 77–92.

[28] Nekoei, A., and Weber, A. (2017). Does extending unemployment benefits improve job quality? *American Economic Review*, 107(2), 527–561.

[29] Soylu, Ö. B., Çakmak, İ., and Okur, F. (2018). Economic growth and unemployment issue: Panel data analysis in Eastern European Countries. *Journal of International Studies*, 11(1), 93–107.

[30] Suleiman, S., Hemed, I., and Kassim, S. T. (2017). Unemployment and economic growth in Tanzania. *Journal of Economics, Management and Trade*, 20(2), 1–8, Article JEMT.38500.