ISSN: 2755-0214

Journal of Economics & Management Research

SCIENTIFIC Research and Community

Review Article

Open Access

Artificial Intelligence and the Transformation of the Growth–Employment Nexus: An Empirical Reappraisal of Okun's Law

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ABSTRACT

This paper examines the impact of artificial intelligence (AI) and technological progress on the relationship between economic growth and unemployment, traditionally described by Okun's law. Using panel data for 11 developed countries over the period 2000–2024, the analysis relies on fixed-effects models and dynamic specifications estimated through the System Generalized Method of Moments (System-GMM). Technological intensity is proxied by an information and communication technology (ICT) index, and an interaction term is introduced to assess its moderating role in the growth–employment relationship.

The results confirm the short-run validity of Okun's law, as economic growth exerts a negative and statistically significant effect on changes in unemployment. However, technological intensity has a positive direct effect on unemployment and weakens the ability of growth to reduce unemployment, suggesting adjustment costs related to automation. Overall, the findings point to a structural transformation of the growth–employment nexus and highlight the need for active policies in skills development and labor market adjustment to ensure more inclusive growth.

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Received: February 05, 2026; **Accepted:** February 11, 2026; **Published:** February 21, 2026

Keywords: Artificial Intelligence, Economic Growth, Unemployment, Okun's Law, Automation

Introduction

The question of artificial intelligence (AI) is an old problem, addressed for several decades. Since the post-war period, thinkers like laid the foundations of automatic control and cybernetics, while in the 1950s, figures such as Alan Turing, John McCarthy, and Marvin Minsky formalized the idea that it would be possible to build machines capable of performing so-called "intelligent" tasks. Long confined to experimental applications, AI has now entered a phase of massive and systemic diffusion [1].

Indeed, the contemporary economic world is moving towards a generalized use of AI: industrial automation, predictive analytics, generative artificial intelligence, and robotization of services, logistical and decision-making optimization. This technological wave now constitutes a structural driver of global economic growth. The investments made illustrate the scale of the phenomenon: major global technology companies have announced unprecedented amounts, such as Amazon (nearly 100 billion USD for data centers), Microsoft (80 billion USD), Google (75 billion USD), Meta (over 600 billion USD over three years), or Apple (500 billion USD over four years).

Globally, AI investment spending is estimated at over 420 billion USD in 2025, 570 billion in 2026, and could exceed 1,300 billion USD by 2030, with an annual growth rate exceeding 20%.

These massive investments reflect the anticipation of considerable productivity gains. AI increases capital efficiency, accelerates innovation, and profoundly modifies production functions. In the United States, intellectual property assets of which AI is now a central pillar represent approximately 7% of GDP, compared to less than 2% thirty years ago, signaling a structural transformation of the economy.

Several macroeconomic studies thus estimate that AI could generate an additional global GDP of several thousands to several tens of thousands of billions of dollars by 2030.

However, this growth dynamic is accompanied by increasing tension in the labor market. Advanced automation and AI systems are substituting a growing number of tasks, including cognitive and intermediate ones, previously performed by human workers. This substitution is already resulting in significant employment adjustments: since 2022, many technology companies have carried out waves of layoffs, in a context combining automation, restructuring, and correction after a phase of over-hiring. As an illustration, the BT group announced reductions of up to 55,000 positions by 2030, largely linked to automation and AI.

Furthermore, the financial and stock market gains associated with AI are extremely concentrated. Since 2022, a handful of large technology companies linked to AI have accounted for nearly 80% of the S&P 500's gains, and the technology sector now accounts for approximately 25% of that index's profits, compared to 5%

three decades ago. This concentration reinforces concerns about an uneven diffusion of AI benefits, both between companies and between countries.

Public and private investments in AI are indeed highly asymmetrical globally. The United States and a few large multinational firms capture the bulk of funding, while many developing countries remain on the sidelines due to a lack of digital infrastructure, skilled human capital, and adapted innovation ecosystems. This configuration raises fears that productivity gains linked to AI will be primarily appropriated by already advanced economies, thus exacerbating international divides and structural inequalities.

In this context, AI simultaneously appears as a major lever for growth and as a factor of profound recomposition of the labor market, questioning the traditional relationships between growth and employment. Therefore, a central question arises: how does artificial intelligence modify the paradigm of economic growth by affecting unemployment? In other words, to what extent can AI be both a driver of growth and a source of destruction, but also of transformation, of jobs, and what are the implications for unemployment dynamics in the short and long term?

Hypothesis

We Formulate the following Hypothesis, Summarized in Two Short-Term and Long-Term Components

- **Short-Term Growth ↔ Employment Dissociation:** Traditionally, Okun's law implies: $\Delta y > 0$; $\Delta u < 0$. In a context where Y=f(L). With the extensive introduction of AI, production can grow without a corresponding increase in unskilled employment, hence an observed scenario where: $\Delta y > 0$; $\Delta u \sim 0$. Consequently, Y=f(A).

- **Long Term:** If AI becomes sufficiently capable of replacing cognitive and non- cognitive tasks, growth can be accompanied by a structural increase in unemployment for certain categories (substitution) while opportunities are created for highly skilled jobs (complementarity). We can then observe: $\Delta y > 0$; $\Delta u > 0$ (for a large fraction of the unskilled workforce), A being a function of a highly skilled workforce: $A=\pi(l) \Rightarrow Y=f\{\pi(l)\}$.

Expected Consequences: job polarization (decline in routine jobs, increase in highly skilled jobs), pressure on wages for automatable tasks, rising inequalities if access to training and human capital remains unequal.

Objective of the Work

The objective of this work is to examine the impact of artificial intelligence as a major determinant of economic growth; while analyzing the threats it poses to employment in the short and long term. It also aims to show the necessity of rapid adaptation of economies and public policies in the face of this dual reality: a driver of productivity and growth on the one hand, and a factor of substitution and reorganization of the labor market on the other.

Literature Review

The impact of artificial intelligence (AI) and automation on economic growth and the labor market is a central theme in recent literature. Several empirical and theoretical works show that AI modifies the traditional dynamics between growth and employment, questioning the universal validity of Okun's law in contemporary economies.

Effects of Automation on Okun's Law

Analyze a panel of 35 OECD countries over the period 1996-2020 and show that robotization significantly modifies the relationship between economic growth and unemployment [2]. The authors find that, in countries highly exposed to automation, the classic negative correlation between GDP variation and unemployment variation is attenuated. This study illustrates that sustained economic growth can be accompanied by an increase in unemployment or stagnation of employment in certain segments of the labor market, thus confirming the idea of a structural break in the classic Okun's paradigm.

Diversity of AI Effects : Automation Versus Augmentation

Other works, such as those by distinguish the effect of automation AI from that of augmentation AI [3]. Automation AI tends to substitute human labor, particularly in low-skilled jobs, while augmentation AI promotes efficiency and the creation of new tasks in skilled professions. This distinction highlights that the impact of AI on the labor market is not uniform and depends on the nature of the technologies deployed as well as the skills available in the economy.

Job Polarization and Redistribution

Complementary literature highlights job polarization induced by AI and digital technologies. Comparative studies; recent work on the American and Indian labor markets show that routine and intermediate jobs are most exposed to automation, while highly skilled or very specialized jobs experience an increase in demand [4].

Contemporary Debates and Policy Implications

Finally, several recent analyses emphasize that the impact of AI is contextual and heterogeneous across sectors, regions, and worker groups [5,6]. While AI can generate productivity gains and create new employment opportunities, it also constitutes a factor of maladjustment in the labor market, particularly for low-skilled or routine jobs. These results reinforce the need to adapt public policies, particularly in terms of training, professional retraining, and technological regulation, to leverage the benefits of AI while limiting its negative externalities.

Research Methodology

In this study, we adopted a quantitative approach, based on econometric analysis, to examine the impact of technological progress on the relationship between economic growth and unemployment, traditionally described by Okun's law. This methodological choice is justified by the very nature of the problem, which aims to empirically test the hypothesis that the intensification of advanced technologies, particularly artificial intelligence, modifies the classic mechanisms of job creation.

Data Selection

We used panel data for 11 observed countries (United States, Germany, France, Japan, South Korea, United Kingdom, Canada, China, Switzerland, Sweden, Singapore) over the period 2000–2024, totaling 231 observations. The choice of this data structure allowed us to combine the temporal and individual dimensions, while taking into account the specificities of each country.

We Favored this Approach Because it Allows

- To control unobservable heterogeneity between countries, particularly related to institutional and structural differences in labor markets
- To improve the statistical robustness of the estimates;
- To better capture the differentiated effects of technological progress over time and space.

The period 2000–2024 was chosen due to its economic and technological importance. It corresponds to a phase of acceleration of digital progress, marked by the diffusion of information technologies, the automation of production processes, and, more recently, the emergence of artificial intelligence applications. This period also includes several major economic cycles, which ensures sufficient data variability for econometric analysis [7-10].

Choice and Justification of Variables

To analyze the relationship between growth, technology, and unemployment, we selected a set of variables consistent with economic literature.

We chose the unemployment rate as the dependent variable, as it is the central indicator of the labor market in analyses inspired by Okun's law. This choice allows for a direct evaluation of economic growth's ability to generate jobs.

As the main explanatory variable, we chose the real GDP growth rate, in accordance with the classic formulation of Okun's law. Theoretically, an increase in economic growth is supposed to lead to a decrease in unemployment. However, the persistence of unemployment in some economies during periods of sustained growth justifies questioning this mechanical relationship.

To capture the effect of technological progress, we used an Information and Communication Technology (ICT) index as a proxy for advanced technological intensity. This choice is explained by the absence of homogeneous and comparable data on artificial intelligence stricto sensu over a long period and for a wide range of countries. The ICT index is thus interpreted as an indirect but relevant measure of the diffusion of advanced technologies, including AI, in the economy. It reflects the level of adoption and use of digital tools and infrastructure that are prerequisites for AI implementation and development.

We also introduced an interaction term between the real GDP growth rate and the ICT index. This term is crucial for assessing the moderating role of technological intensity on the growth-employment relationship. Our hypothesis is that, as technological intensity increases, the ability of economic growth to reduce unemployment may be attenuated, or even reversed, due to automation and the substitution of labor by capital.

Finally, we included control variables commonly used in the literature to account for other factors influencing unemployment, such as inflation, interest rates, and labor market rigidities. These variables help to isolate the specific effect of technological progress and economic growth on unemployment [11-13].

Econometric Model Specification

To ensure the reliability and robustness of our conclusions, we adopted a stepwise modeling approach. The fixed-effects model serves as our benchmark specification for identifying short-term elasticities. The introduction of an interaction term then allows us to capture the technological impact according to the economic cycle. Finally, the use of the system GMM estimator confirms the persistence of our results in the face of potential endogeneity biases. We aim to capture the disruptive effect of AI.

Based on the Selected Variables, We Specified the Following Econometric Models:

a. The Fixed Effects Model (Static Without Interaction)

$\Delta Uit = \alpha i + \beta \Delta yit + \gamma ICTit + \mu i + \tau t + \varepsilon it$

b. The fixed effects model (static with interaction)

$\Delta Uit = \alpha i + \beta \Delta yit + \gamma ICTit + \delta(\Delta yit \times ICTit) + \mu i + \tau t + \varepsilon it$

c. The fixed effects model (dynamic without interaction)

$\Delta Uit = p\Delta Ui,t{-}1 + \beta \Delta yit + \gamma ICTit + \mu i + \tau t + \varepsilon it$

d. The Fixed Effects Model (Dynamic with Interaction)

$\Delta Uit = p\Delta Ui,t{-}1 + \beta \Delta yit + \gamma ICTit + \delta(\Delta yit \times ICTit) + \mu i + \tau t + \varepsilon it$

Where

- ΔU_{it}: Dependent variable, a first difference of the unemployment rate, used to measure labor market performance.
- g_{it} **:** GDP growth, GDP growth, which captures the cyclical dynamics of economic activity.
- ICT_{it} : AI proxy, used as a proxy for AI adoption and reflecting structural technological progress.
- $g_{it} \times ICT_{it}$ **:** Interaction term between growth and ICT, used to test the hypothesis of jobless growth.
- $\alpha_i + \beta \Delta y_{it}$**:** Standard effect of growth on unemployment (Okun's Law).
- γICT_{it}**:** Direct effect of AI.
- $\delta(\Delta y_{it} \times ICT_{it})$: Moderating effect of AI on the growth–employment relationship.
- $p\Delta U_{it-1}$ **:** Model dynamics on the relationship.
- $\mu_i + \tau_t$ **:** Individual and time effects of the model.
- ε_{it} **:** is the error term

This Specification Allows us to Distinguish

- The direct effect of economic growth on unemployment;
- The specific effect of technological progress;
- The conditional effect of growth in the presence of advanced technologies.

Estimation Method

The choice of econometric strategy is based on a prioritization of models aimed at isolating the effect of artificial intelligence on unemployment dynamics while ensuring the convergence of the estimators. For the static specifications intended to capture short-term elasticities, we implement the within transformation method. This procedure consists of centering the variables on their respective time averages in order to purge the model of unobserved individual fixed effects, thereby neutralizing biases related to the structural and institutional specificities of each country that remain constant over the period studied [14-17].

At the same time, taking into account the time dimension and the persistence of shocks in the labor market requires the use of dynamic modeling that incorporates the lagged dependent variable. In this setup, the within transformation estimator becomes biased due to the correlation between the lagged variable and the error term. To address this Nickell bias and handle the potential endogeneity of growth and technology variables, we use the System Generalized Method of Moments (System-GMM) estimator. This method simultaneously combines first-difference equations, instrumented by lagged levels, and level equations, instrumented by first differences, providing greater statistical efficiency than simple-difference GMM, especially when the variables exhibit strong persistence.

Finally, in order to ensure the validity of the statistical inference in the face of classical panel data failures, all our estimates are made using robust standard errors. This White's correction approach allows to obtain consistent variance-covariance even in the presence of heteroscedasticity and autocorrelation of residuals within national blocks. This dual requirement, combining internal instruments via GMM and robustness of standard errors, makes it possible to stabilize the interaction coefficients and to guarantee that the observed results are not the product of measurement biases or spatial correlations between the economies of our sample.

Methodological Scope of the Study

This study focuses on a specific set of developed countries and a defined time period, allowing for a detailed analysis of the AI impact within these contexts. While the findings provide valuable insights, their generalizability to developing countries or different timeframes should be considered with caution. The choice of the ICT index as a proxy for AI intensity is a pragmatic one, acknowledging data limitations but ensuring a robust measure of technological advancement relevant to the study's objectives [18-20].

Exploratory Data Analysis

Overall Descriptive Statistics

Table 1: Statistics Descriptive of Panel (Overall Variations, between and within)

Variable		Mean	Std. dev.	Min	Max	Observations
Delta_~t	overall	-.0647186	.7829953	-2.706	4.386	N = 231
	between		.100734	-.3034762	.087381	n = 11
	within		.7770564	-2.681052	4.410948	T = 21
GDP_gr~h	overall	2.611822	3.288161	-10.0479	14.51975	N = 231
	between		2.148296	.6193692	8.02615	n = 11
	within		2.568686	-8.880848	12.20442	T = 21
IA_pro~T	overall	12.29742	6.879544	3.495191	39.21	N = 231
	between		6.763539	4.740575	26.73608	n = 11
	within		2.358077	-3.178651	24.77135	T = 21
Inflat~n	overall	1.917702	1.765394	-1.352837	8.548625	N = 231
	between		.7158469	.5643801	2.663347	n = 11
	within		1.627495	-1.143174	8.513501	T = 21
Trade_~s	overall	4.338952	8.781891	-5.692505	39.87901	N = 231
	between		8.907515	-3.637245	28.89364	n = 11
	within		2.162694	-3.893861	15.32433	T = 21

Note: Authors work on Stata 18 using data from the World Bank

The table of descriptive statistics revealed a structure of balanced panels from a sample (N=231 observations across 11 countries). It is noted that for the dependent variable, the within (intra-country) variation of 0.77 is much higher than the between (inter-country) variation of 0.100, which will justify the use of a Fixed Effects model, as will be confirmed by additional tests.

Bi-Various Relationships

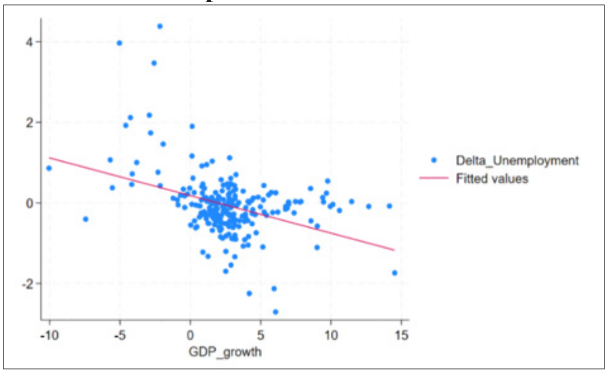

Figure 1: Unemployment Varies to Growth

Note: Authors work on Stata 18 using data from the World Bank

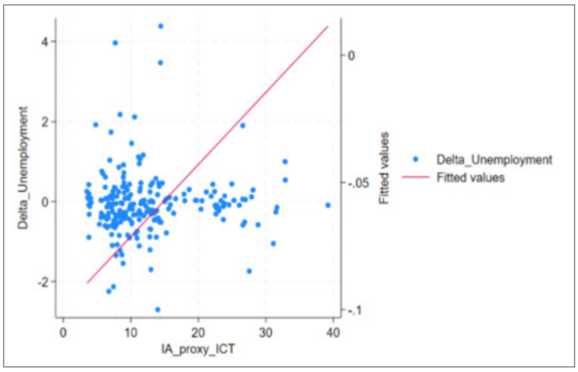

Figure 2: Unemployment Varies to lA Proxy

Note: Authors work on Stata 18 using data from the World Bank

These graphs visually illustrate our hypotheses. A clear negative slope is observed, which visually validates Okun's law. That is, when growth increases, the change in unemployment decreases. The points are relatively clustered around the regression line, confirming the strong significance of this variable. Conversely, the slope in Figure 2 is positive. This illustrates that in our sample, the increase in digital infrastructure seems to be correlated with a short-term rise in unemployment, possibly due to a capital-labor substitution effect [21].

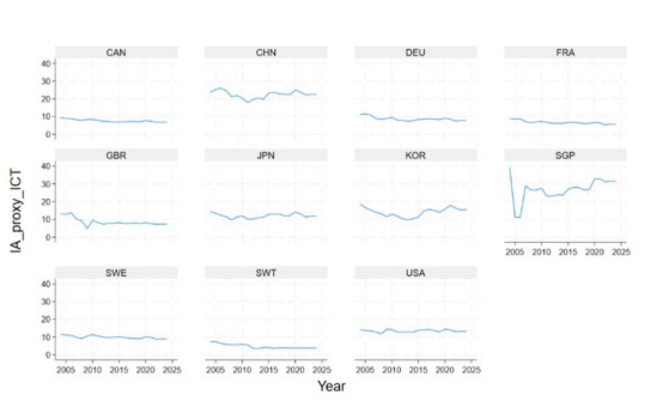

Figure 3: Comparative Evolution ICT/Country **Figure 4:** Comparative Evolution GDP/Country

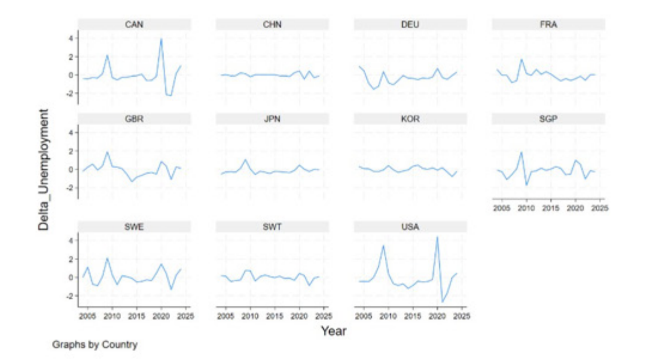

Figure 5: Comparative Evolution Unemployment/Country **Figure 6:** Comparative Inflation/Country

The exploratory country-by-country chart highlights a strong synchronization of macroeconomic variables around major global shocks, notably the 2008-2009 financial crisis and the 2020 pandemic. This synchronization suggests the existence of common shocks affecting all of the economies studied simultaneously, justifying the introduction of time-fixed effects in econometric estimates.

The ICT variable, used as a proxy for the adoption of artificial intelligence, shows a generally smooth and increasing trajectory across all countries, with marked heterogeneity in levels. This behavior is consistent with the structural and cumulative nature of technological progress, as opposed to cyclical macroeconomic variables such as growth or inflation. Finally, GDP growth appears to be highly volatile and centered around zero, with no persistent trend, which is consistent with the hypothesis of stationarity for the series used in the analysis

Figure 7: Visualization of Technological Heterogeneity

Note: Authors work on Stata 18 using data from the World Bank

The boxplot reveals major structural disparities within our sample of 11 countries. Countries like Singapore and China show technology adoption levels significantly above the panel average, with medians around 35 and 25, respectively. In contrast, economies like Canada or France have more modest levels and very low variance.

Presentation and Analysis of Econometric Results

Table 2: Results of the FE Model Regression without Interaction (Robust Standard Errors)

Fixed-effects (within) regression — Number of obs = 231
Group variable: Id_Country — Number of groups = 11

R-squared: Within = 0.3258; Between = 0.1707; Overall = 0.2337
Obs per group: min = 21; avg = 21.0; max = 21

F(4, 10) = 4.50
corr(u_i, Xb) = -0.4256 — Prob > F = 0.0244

(Std. err. adjusted for 11 clusters in Id_Country)

Delta_Unempl~t	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
GDP_growth	-.1482259	.0417921	-3.55	0.005	-.2413446	-.0551073
IA_proxy_ICT	.0260163	.0077971	3.34	0.008	.0086434	.0433893
Inflation	-.0932364	.0345182	-2.70	0.022	-.1701477	-.0163251
Trade_openness	.004274	.0261549	0.16	0.873	-.0540028	.0625509
_cons	.1627422	.1830915	0.89	0.395	-.245211	.5706955
sigma_u	.28959063					
sigma_e	.65840206					
rho	.1620987	(fraction of variance due to u_i)				

Note: Calculations performed by the authors on Stata 18

Table 3: Results of the FE Model Regression with Interaction (Robust Standard Errors)

Fixed-effects (within) regression — Number of obs = 231
Group variable: Id_Country — Number of groups = 11

R-squared: Within = 0.3382; Between = 0.1579; Overall = 0.2461
Obs per group: min = 21; avg = 21.0; max = 21

F(5, 10) = 4.05
corr(u_i, Xb) = -0.4188 — Prob > F = 0.0286

(Std. err. adjusted for 11 clusters in Id_Country)

Delta_Unemployment	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
GDP_growth	-.2002347	.0716243	-2.80	0.019	-.3598235	-.0406459
IA_proxy_ICT	.0078616	.020898	0.38	0.715	-.0387021	.0544253
Inflation	-.0935016	.0339862	-2.75	0.020	-.1692276	-.0177755
Trade_openness	.0049481	.0226374	0.22	0.831	-.0454912	.0553874
c.GDP_growth#c.IA_proxy_ICT	.0034935	.0026884	1.30	0.223	-.0024967	.0094837
_cons	.3702298	.3281395	1.13	0.286	-.3609107	1.10137
sigma_u	.28835248					
sigma_e	.65381193					

Note: Calculations performed by the authors on Stata 18

Table 4: Results of Dynamic Regression without Interaction (Robust Standard Errors)

```
Group variable: id_country                      Number of groups  =         11
Time variable: Year
                                                Obs per group:
                                                             min =         20
                                                             avg =         20
                                                             max =         20

Number of instruments =    209                  Wald chi2(5)      =      49.23
                                                Prob > chi2       =     0.0000
Two-step results
```

Delta_Unemployment	Coefficient	WC-robust std. err.	z	P>|z|	[95% conf.	interval]
Delta_Unemployment L1.	.0834203	.1693744	0.49	0.622	-.2485474	.415388
Trade_openness	-.0627553	.1392212	-0.45	0.652	-.3356239	.2101132
IA_proxy_ICT	.0715279	.1031067	0.69	0.488	-.1305575	.2736134
Inflation	-.060927	.0913436	-0.67	0.505	-.2399571	.1181031
GDP_growth	-.1504762	.0491389	-3.06	0.002	-.2467867	-.0541656
_cons	-.1282628	1.000367	-0.13	0.898	-2.088946	1.83242

```
Instruments for differenced equation
        GMM-type: L(2/3).Delta_Unemployment L(2/2).Trade_openness
                  L(2/2).IA_proxy_ICT L(2/2).Inflation L(2/2).GDP_growth
Instruments for level equation
        GMM-type: LD.Delta_Unemployment LD.Trade_openness LD.IA_proxy_ICT
                  LD.Inflation LD.GDP_growth
        Standard:  cons
```

Note: Calculations performed by the authors on Stata 18

Table 5: Results of Dynamic Regression with Interaction (Robust Standard Errors)

```
Number of instruments =    252                  Wald chi2(5)      =      75.68
                                                Prob > chi2       =     0.0000
Two-step results
```

Delta_Unemployment	Coefficient	WC-robust std. err.	z	P>|z|	[95% conf.	interval]
Delta_Unemployment L1.	-.0281946	.3182003	-0.09	0.929	-.6518558	.5954666
Trade_openness	-.1751522	.1520898	-1.15	0.249	-.4732427	.1229383
Inflation	-.1239874	.1062471	-1.17	0.243	-.3322279	.0842531
IA_GDP	.0011281	.0045138	0.25	0.803	-.0077187	.009975
IA_proxy_ICT	.2301321	.1870821	1.23	0.219	-.1365421	.5968062
GDP_growth	-.1522264	.0826691	-1.84	0.066	-.3142549	.0098021
_cons	-1.176491	1.316423	-0.89	0.371	-3.756634	1.403651

```
Instruments for differenced equation
        GMM-type: L(2/3).Delta_Unemployment L(2/2).Trade_openness L(2/2).Inflation
                  L(2/2).IA_GDP L(2/2).IA_proxy_ICT L(2/2).GDP_growth
        Standard: D.GDP_growth D.IA_proxy_ICT D.Inflation D.Trade_openness
                  D.IA_GDP
Instruments for level equation
        GMM-type: LD.Delta_Unemployment LD.Trade_openness LD.Inflation LD.IA_GDP
                  LD.IA_proxy_ICT LD.GDP_growth
        Standard:  cons
```

Note: Calculations performed by the authors on Stata 18

Interpretation of Econometric Results

This section analyzes the results from the various estimated econometric specifications in order to assess the empirical validity of Okun's law and to examine the moderating role of technological intensity on the relationship between economic growth and unemployment. The estimates are based on fixed effects (FE) panel models as well as dynamic models estimated using the system GMM method, both with and without interaction terms.

Overall Quality and Statistical Validity of Models

The fixed-effects models have a Within R-squared ranging from 32.5% to 33.8%. This result indicates that the chosen explanatory variables help explain about one-third of the fluctuations in unemployment around each country's own mean. It should be noted that, in a fixed-effects panel framework, the Within R-squared measures exclusively the model's ability to explain within-country variance, and not the differences in levels between countries.

In cyclical macroeconomic models applied to aggregate data, such values are generally considered satisfactory, given the high volatility inherent in labor markets and the role of unobserved shocks.

Furthermore, the overall significance tests (F-test for FE models and Wald test for dynamic models) confirm that the included variables are jointly significant, thus validating the relevance of the chosen econometric framework.

Empirical Validation of Okun's law

The most robust and stable result across all specifications concerns the effect of economic growth on changes in unemployment. In the fixed-effects models (Table 2), the coefficient associated with GDP growth rate is negative and highly significant (Coef = -0.15, $p < .005$). This result implies that a one-percentage-point increase in the economic growth rate is, on average, associated with a decrease of about 0.15 percentage points in the change in the unemployment rate.

This finding constitutes clear empirical validation of Okun's law in a multi-country panel framework, confirming the existence of a negative cyclical relationship between economic activity and unemployment. The stability of the sign and significance of this coefficient in dynamic models (Table 4) reinforces the idea that growth remains the main driver of unemployment reduction in the short and medium term in the countries studied (Coef = - 0.15, $p < .002$).

Direct Effect of Technological Intensity (AI / ICT)

The results of the fixed-effects models (Table 2) highlight a positive and statistically significant direct effect of technological intensity, measured by the ICT/AI proxy, on the change in unemployment. This result (Coef = 0.02, $p < .008$) suggests that, over the considered time horizon, an increase in the adoption of digital technologies is associated with a temporary rise in unemployment.

From an economic point of view, this relationship can be interpreted as reflecting labor market adjustment processes related to technological transition. Automation and the spread of digital technologies can, in the short term, generate capital-for-labor substitution effects as well as skill mismatch phenomena, before productivity gains translate into the creation of new jobs, notably through adjustments in government employment policies. It is important to emphasize that this effect should not be interpreted as a structural or permanent impact of technology on unemployment, but rather as an average short- to medium-term effect captured by the model.

Interaction Between Economic Growth and Technological Intensity

The introduction of an interaction term between GDP growth and technological intensity (Table 3 & Table 5) allows us to examine whether technology modifies the ability of growth to reduce unemployment.

In the static model (Coef = 0.0034, $p < .223$) and the dynamic model (Coef = 0.0011, $p < .803$). These results indicate that this interaction term is positive and weakly significant, suggesting that the negative effect of growth on unemployment tends to diminish when the level of technological intensity is higher.

Formally, the marginal effect of growth on the change in unemployment can b as:

$$\frac{\partial \Delta u}{\partial g} = \beta_1 + \beta_3 \times IC$$

Contributions and Limitations of Dynamic Models (GMM)

Dynamic estimates using the system GMM method reveal a loss of significance for several explanatory variables, with the exception of economic growth, which remains significant in certain specifications. This change in results can be explained by several factors. Firstly, the very high number of instruments relative to the number of countries (11 groups for more than 200 instruments in some specifications) suggests an issue of instrument proliferation, well documented in the methodological literature. This situation can weaken the power of over- identification tests and lead to inflation of standard errors, mechanically reducing the significance of the estimated coefficients.

Secondly, the coefficient associated with the lagged variable of the change in unemployment is low and not significant, indicating an absence of pronounced persistence in annual unemployment fluctuations. This result suggests that, in the studied sample, labor market adjustments are relatively swift and that the dynamics of unemployment are mainly explained by contemporary variables rather than past inertia. In this context, dynamic models should be interpreted primarily as robustness tests aimed at addressing potential endogeneity issues, rather than as core specifications.

Economic Summary of Results

Overall, the empirical results highlight three major lessons. First, economic growth appears to be the most robust and systematic lever for reducing unemployment, confirming the relevance of Okun's law in a multi-country panel framework.

Secondly, technological intensity has a direct positive effect on short-term unemployment, suggesting that the digital transition can create adjustment costs in the labor market. Thirdly, the interaction between growth and technology indicates that the spread of AI and ICT can weaken the ability of growth to generate jobs, reinforcing the idea that technological innovation must be accompanied by active training and skills adaptation policies.

In light of these results, fixed-effects models are retained as the main framework for analyzing short-term dynamics, while dynamic GMM estimates are used as robustness tools, taking into account the limitations related to sample size and instrument complexity.

Marginal Effects and Economic Interpretation

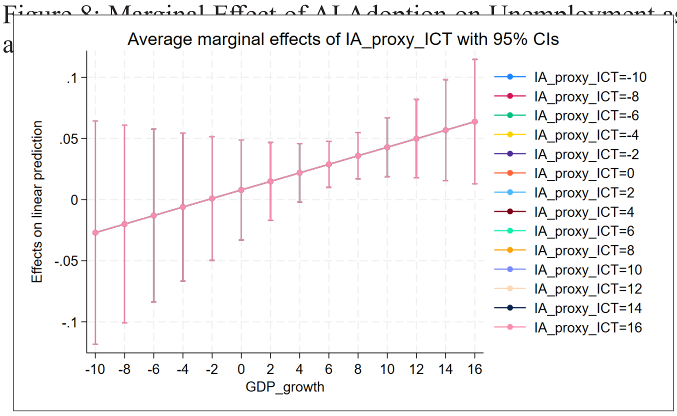

Figure 8: Marginal Effect of AI Adoption on Unemployment as a Function of GDP Growth Rate

Note: Calculations performed by the authors on Stata 18

The positive slope of the estimated curve indicates that the marginal effect of AI on unemployment gradually becomes higher and therefore more detrimental to employment as the GDP growth rate increases. In other words, economic growth does not automatically neutralize the impact of AI; on the contrary, it can amplify its effects on the labor market.

From an economic perspective, two distinct regimes clearly emerge.
In periods of low growth or economic contraction, the marginal effect of AI on unemployment is close to zero, or even slightly negative. However, the confidence intervals are wide and include zero, which suggests the absence of a statistically well-defined relationship. In this regime, AI adoption remains limited. On the other hand, when the economy enters a period of strong expansion (> 6%), the marginal effect of AI becomes positively significant.

This configuration validates the central hypothesis of the study: during periods of sustained growth, companies intensify their investments in automation and AI technologies in order to maximize productivity gains. These investments primarily promote the accumulation of technological capital and the optimization of production processes, to the detriment of employment, particularly for routine and low-skilled tasks. Thus, this figure highlights a break from the traditional paradigm of growth that creates jobs.

Economic growth here acts not as a systematic buffer against unemployment, but as an accelerator of the effects of technological substitution. This result suggests that the relationship between growth and employment becomes conditional on the technological regime, confirming the idea that Okun's law is now modulated by the intensity of AI adoption.

Conclusion

This study aimed to analyze the impact of artificial intelligence and digital infrastructure on unemployment dynamics, while reassessing the empirical validity of Okun's law in a context of deep technological transition. By using panel data for a set of developed countries over a recent period, our approach sought to confront the traditional labor market mechanisms with the changes induced by the gradual adoption of AI technologies.

Empirical Teaching and Hypothesis Validation

The results obtained first of all confirm the short-term resilience of Okun's law. GDP growth remains a central determinant of unemployment reduction, as indicated by the negative and statistically significant coefficient estimated across all static specifications. This robust negative relationship suggests that, despite technological changes, the cyclical dynamics of economic activity continue to play a key role in labor market adjustment.

At the same time, the study highlights a significant positive effect of the ICT/AI proxy on unemployment, which supports the hypothesis of a short-term substitution effect. This result suggests that automation and the spread of digital technologies initially replace certain types of tasks and jobs, before the complementary effects, the creation of new occupations, and organizational gains fully materialize. Thus, AI appears, at this stage of its adoption cycle, to contribute to a partial decoupling between economic growth and employment. The introduction of interaction terms between growth and AI reinforces this interpretation: technology alters the traditional transmission of growth to employment, without completely nullifying it. Okun's law is therefore not invalidated, but structurally transformed.

Economic Robustness and Methodological Limitations

The robustness of the conclusions relies on a series of diagnostic tests. The absence of excessive multicollinearity (Appendix 4) ensures that the estimated effects of AI are not artificially inflated by linear correlations between explanatory variables. Furthermore, the Arellano-Bond tests (Appendix 4) confirm the absence of second-order autocorrelation in the residuals, thereby validating the chosen dynamic specification.

Nevertheless, the GMM analysis highlights a classic limitation related to the proliferation of instruments, illustrated by a Sargan test p-value equal to 1 (Appendix 4). This loss of statistical power calls for a cautious interpretation of the dynamic results and underscores the methodological difficulty of capturing emerging technological phenomena using panels with a limited cross-sectional dimension.

More fundamentally, this difficulty reflects the very novelty of the dynamics being studied. The adoption of AI in production processes is still heterogeneous, gradual, and often invisible in traditional statistics. The proxy used the imports of ICT goods and services although consistent with existing literature, only imperfectly captures the actual intensity of AI use, its degree of organizational integration, or its complementarity with human capital. This measurement imperfection constitutes a structural limitation of the analysis and opens the door to future improvements.

Economic Implications and Research Perspectives

Overall, the results of this study describe a structural transition phase in the labor market. AI appears simultaneously as a factor of potential productivity and as a source of short- term frictions. The positive relationship observed between AI and unemployment should therefore not be interpreted as a permanent effect, but rather as a reflection of an incomplete adjustment of skills, institutions, and productive structures.

The results of this study suggest that contemporary economies are facing a major structural challenge in terms of employment. Indeed, the rapid spread of artificial intelligence and automation technologies tends to replace a growing number of routine tasks, traditionally performed by human labor. This dynamic increases the risk of structural unemployment, particularly for workers whose skills are poorly suited to new technological requirements.

In this context, economic growth no longer automatically guarantees an improvement in the labor market situation. To mitigate these effects, governments are called upon to undertake deep reforms of education and training systems, directing them towards the development of skills that complement advanced technologies.

It thus becomes necessary to rethink the current educational model to prepare a future workforce that is more flexible, skilled, and competitive, capable of integrating into a labor market characterized by high technological intensity. In particular, specialization in fields related to engineering, data analysis, programming, and solving complex problems appears to be a central lever.

In an economy dominated by artificial intelligence, the demand for labor tends to shift toward profiles capable of manipulating symbols, designing systems, interpreting information, and exercising critical judgment, rather than performing repetitive tasks. Consequently, education constitutes a key economic policy tool to preserve employability and promote more inclusive growth.

APPENDIX

United Sates of America

-> Id_Country = 1

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.0896667	1.554315	-2.706	4.386
GDP_growth	21	2.176432	1.857273	-2.5765	6.055053
IA_proxy_ICT	21	13.45477	.6889358	11.84	14.44
Inflation	21	2.588126	1.757984	-.3555463	8.0028
Trade_open~s	21	-3.637245	1.034504	-5.692505	-2.691998

Germany

-> Id_Country = 2

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.3034762	.6331182	-1.545	.948
GDP_growth	21	1.147544	2.458171	-5.544555	4.134638
IA_proxy_ICT	21	8.732643	1.179427	7.36	11.5
Inflation	21	1.981385	1.660287	.1448779	6.872574
Trade_open~s	21	5.433651	1.177119	2.471054	7.414214

France

-> Id_Country = 3

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.0445714	.5694455	-.824	1.736
GDP_growth	21	1.258581	2.632893	-7.440646	6.882338
IA_proxy_ICT	21	6.745762	.9615244	5.35	8.89
Inflation	21	1.68337	1.349824	.0375144	5.222367
Trade_open~s	21	-.722004	.8400674	-2.730911	1.326443

Japan

-> Id_Country = 4

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.128	.3580406	-.552	1.066
GDP_growth	21	.6193692	2.178032	-5.693236	4.097918
IA_proxy_ICT	21	12.01348	1.26499	9.68	14.49
Inflation	21	.6167016	1.240587	-1.352837	3.268134
Trade_open~s	21	-.2322113	1.511201	-3.720139	1.988176

South Korea

-> Id_Country = 5

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.0176667	.2877545	-.782	.464
GDP_growth	21	3.356643	1.696774	-.7002423	6.981661
IA_proxy_ICT	21	14.114	2.498531	9.79	18.65
Inflation	21	2.428517	1.336933	.3830003	5.089514
Trade_open~s	21	2.769232	1.985814	-.3890528	6.548085

United Kingdom

-> Id_Country = 6

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.0331429	.7182178	-1.341	1.922
GDP_growth	21	1.444773	3.530496	-10.0479	8.543112
IA_proxy_ICT	21	8.651571	2.187497	4.81	13.71
Inflation	21	2.663347	1.778854	.3680468	7.922049
Trade_open~s	21	-1.03228	1.357276	-2.319494	4.073982

Canada

-> Id_Country = 7

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.0535238	1.282403	-2.248	3.967
GDP_growth	21	1.895836	2.303811	-5.038233	5.950528
IA_proxy_ICT	21	7.680324	.7690175	6.75	9.33
Inflation	21	2.165454	1.350107	.2994668	6.802801
Trade_open~s	21	-.3086867	2.13427	-2.46498	4.463123

China

-> Id_Country = 8

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	.0019524	.2146766	-.45	.44
GDP_growth	21	8.02615	2.924529	2.340188	14.14999
IA_proxy_ICT	21	22.46765	2.041659	18	26.07
Inflation	21	2.332711	1.666613	-.7281653	5.925251
Trade_open~s	21	3.222029	2.273781	-.2623728	8.546927

Switzerland

-> Id_Country = 9

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.0003333	.3822115	-.891	.759
GDP_growth	21	1.993141	1.812667	-2.297375	5.55962
IA_proxy_ICT	21	4.740575	1.288565	3.495191	7.405697
Inflation	21	.5643881	1.037806	-1.143989	2.835828
Trade_open~s	21	9.329994	2.089036	5.447176	13.77884

Sweden

-> Id_Country = 10

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	.087381	.8233851	-1.33	2.116
GDP_growth	21	1.884423	2.473502	-4.255614	5.750765
IA_proxy_ICT	21	9.934819	.8431919	8.69	11.55
Inflation	21	1.952826	2.421556	-.4944605	8.548625
Trade_open~s	21	4.012275	1.630305	1.472989	6.866434

Singapore

-> Id_Country = 11

Variable	Obs	Mean	Std. dev.	Min	Max
Delta_Unem~t	21	-.1308571	.7492495	-1.74	1.9
GDP_growth	21	4.927152	4.017723	-3.814709	14.51975
IA_proxy_ICT	21	26.73608	6.434029	11.26	39.21
Inflation	21	2.117908	2.181583	-.5298098	6.635441
Trade_open~s	21	28.89364	5.080382	20.66083	39.87901

```
Im-Pesaran-Shin unit-root test for Unemployment_rate

H0: All panels contain unit roots           Number of panels  =     11
Ha: Some panels are stationary              Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                   sequentially
Time trend:   Not included                  Cross-sectional means removed

ADF regressions: 0.36 lags average (chosen by AIC)

                     Statistic      p-value
W-t-bar               -2.6747        0.0037
```

```
Im-Pesaran-Shin unit-root test for Delta_Unemployment

H0: All panels contain unit roots           Number of panels  =     11
Ha: Some panels are stationary              Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                   sequentially
Time trend:   Not included                  Cross-sectional means removed

ADF regressions: 0.55 lags average (chosen by AIC)

                     Statistic      p-value
W-t-bar               -9.4263        0.0000
```

```
Im-Pesaran-Shin unit-root test for IA_proxy_ICT

H0: All panels contain unit roots           Number of panels  =     11
Ha: Some panels are stationary              Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                   sequentially
Time trend:   Included                      Cross-sectional means removed

ADF regressions: 0.36 lags average (chosen by AIC)

                     Statistic      p-value
W-t-bar               -8.1867        0.0000
```

```
Im-Pesaran-Shin unit-root test for Inflation

H0: All panels contain unit roots           Number of panels  =     11
Ha: Some panels are stationary              Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                   sequentially
Time trend:   Not included                  Cross-sectional means removed

ADF regressions: 0.27 lags average (chosen by AIC)

                     Statistic      p-value
W-t-bar               -5.5274        0.0000
```

```
Im-Pesaran-Shin unit-root test for GDP_growth

H0: All panels contain unit roots           Number of panels  =     11
Ha: Some panels are stationary              Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                   sequentially
Time trend:   Not included                  Cross-sectional means removed

ADF regressions: 0.27 lags average (chosen by AIC)

                     Statistic      p-value
W-t-bar               -7.8740        0.0000
```

```
Im-Pesaran-Shin unit-root test for Trade_openness

H0: All panels contain unit roots           Number of panels  =     11
Ha: Some panels are stationary              Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T,N -> Infinity
Panel means:  Included                                   sequentially
Time trend:   Not included                  Cross-sectional means removed

ADF regressions: 0.27 lags average (chosen by AIC)

                     Statistic      p-value
W-t-bar               -1.8347        0.0333
```

Appendix 4: Model validation

```
Fisher-type unit-root test for GDP_growth
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots           Number of panels  =     11
Ha: At least one panel is stationary        Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included                  Cross-sectional means removed
Drift term:   Included                      ADF regressions: 1 lag

                                   Statistic      p-value

 Inverse chi-squared(22)   P        115.8220       0.0000
 Inverse normal            Z         -8.1781       0.0000
 Inverse logit t(59)       L*        -9.6596       0.0000
 Modified inv. chi-squared Pm        14.1442       0.0000

 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
```

```
Fisher-type unit-root test for Unemployment_rate
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots           Number of panels  =     11
Ha: At least one panel is stationary        Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included                  Cross-sectional means removed
Drift term:   Included                      ADF regressions: 1 lag

                                   Statistic      p-value

 Inverse chi-squared(22)   P         86.8207       0.0000
 Inverse normal            Z         -6.0987       0.0000
 Inverse logit t(59)       L*        -7.0408       0.0000
 Modified inv. chi-squared Pm         9.7721       0.0000

 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
```

```
Fisher-type unit-root test for Delta_Unemployment
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots           Number of panels  =     11
Ha: At least one panel is stationary        Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included                  Cross-sectional means removed
Drift term:   Included                      ADF regressions: 1 lag

                                   Statistic      p-value

 Inverse chi-squared(22)   P        149.3834       0.0000
 Inverse normal            Z         -9.9198       0.0000
 Inverse logit t(59)       L*       -12.5129       0.0000
 Modified inv. chi-squared Pm        19.2038       0.0000

 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
```

```
Fisher-type unit-root test for Inflation
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots           Number of panels  =     11
Ha: At least one panel is stationary        Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included                  Cross-sectional means removed
Drift term:   Included                      ADF regressions: 1 lag

                                   Statistic      p-value

 Inverse chi-squared(22)   P        113.1428       0.0000
 Inverse normal            Z         -8.2997       0.0000
 Inverse logit t(59)       L*        -9.4688       0.0000
 Modified inv. chi-squared Pm        13.7403       0.0000

 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
```

```
Fisher-type unit-root test for Trade_openness
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots           Number of panels  =     11
Ha: At least one panel is stationary        Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included                  Cross-sectional means removed
Drift term:   Included                      ADF regressions: 1 lag

                                   Statistic      p-value

 Inverse chi-squared(22)   P         81.2802       0.0000
 Inverse normal            Z         -6.3166       0.0000
 Inverse logit t(59)       L*        -6.7207       0.0000
 Modified inv. chi-squared Pm         8.9368       0.0000

 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
```

```
Fisher-type unit-root test for IA_proxy_ICT
Based on augmented Dickey-Fuller tests

H0: All panels contain unit roots           Number of panels  =     11
Ha: At least one panel is stationary        Number of periods =     21

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included                  Cross-sectional means removed
Drift term:   Included                      ADF regressions: 1 lag

                                   Statistic      p-value

 Inverse chi-squared(22)   P         86.5440       0.0000
 Inverse normal            Z         -6.5768       0.0000
 Inverse logit t(59)       L*        -7.1721       0.0000
 Modified inv. chi-squared Pm         9.7304       0.0000

 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
```

Appendix 4: Model validation

```
Pesaran's test of cross sectional independence =     3.038, Pr = 0.0024

Average absolute value of the off-diagonal elements =     0.272
```

F test (specification F test)

```
F test that all u_i=0: F(10, 215) = 2.58                 Prob > F = 0.0057
```

Hausman test

```
                 b = Consistent under H0 and Ha; obtained from xtreg.
  B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =  44.68
Prob > chi2 = 0.0000
```

Shapiro-wilk w test

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
residus	231	0.91683	14.073	6.128	0.00000

Arellano-Bond test

Arellano-Bond test for zero au

H0: No autocorrelation

Order	z	Prob > z
1	[illegible]	[illegible]
2		

Sargan test

```
. estat sargan
Sargan test of overidentifying restrictions
H0: Overidentifying restrictions are valid

        chi2(203)     =  5.769439
        Prob > chi2   =    1.0000
```

le la Variance (V

Variable	VIF	1/VIF
GDP_growth	5.13	0.194992
IA_proxy_ICT	2.81	0.355417
Inflation	1.08	0.924905
Trade_open~s	1.49	0.669152
c. GDP_growth# c. IA_proxy_ICT	7.58	0.131965
Mean VIF	3.62	

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