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The Importance of the Autoregressive Distributed Lag (ARDL) Model in Econometric Modeling of Regional Socio-Economic Development

Rajabov Alibek Xushnudbekovich*¹

1. PhD, "Mamun University" Associate Professor of the Department of Economics

* Correspondence: alibek.rajabov@gmail.com

Abstract: In this research work, the short- and long-term effects of independent variables such as industrial production per capita (IP per capita), fixed capital investment per capita (FCI per capita), and the unemployment rate on the dependent variable of gross regional product per capita (GRP per capita) were examined in the context of the Khorezm region in the Republic of Uzbekistan over the period from 2005 to 2024. The Autoregressive Distributed Lag (ARDL) model was employed to identify these effects. According to the findings, industrial production per capita and fixed capital investment per capita exert positive influences on gross regional product per capita in both the short and long term, whereas the unemployment rate demonstrates a negative impact in both periods.

Keywords: Socio-Economic Development, Long-Term, Short-Term, ARDL, Autoregressive, GRP Per Capita, IP Per Capita, FCI Per Capita, ADF, PP, ARDL Bound Test

1. Introduction

The ongoing intensification of globalization processes and the increasing instability of the world, particularly the negative shift in the balance of risks to global economic growth, continue to contribute to uncertainties in the prospective development of the global economy. According to the forecasts of the International Monetary Fund, "global economic growth is expected to slow from 3.3 percent in 2023 to 3.2 percent in 2024 and remain at 3.2 percent in 2025" [1]. This, in turn, necessitates the implementation of effective regional policies aimed at reducing disparities in per capita income across different regions and ensuring sustainable socio-economic development.

Ensuring compatibility between macroeconomic stability and structural reforms, as well as implementing an effective system and mechanisms for managing economic cycles arising from the influence of external and internal factors based on modern forecasting models, demands even greater attention. "For the development of the economy, it is essential to comprehensively and balancedly advance the socio-economic development of provinces, districts, and cities, while effectively and optimally utilizing their potential. At the same time, we must impart a periodic and continuous nature to the evaluation of regions' socio-economic development based on specific criteria" [2]. From this perspective, the efficient utilization of regional potential and the objective assessment of sustainable socio-economic development in regions are regarded as one of the most critical issues of the present day.

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In recent years, substantial attention has been directed in the scholarly works of foreign researchers toward the issues of socio-economic development in regions. For instance, using the example of European Union countries, the impact on sustainable economic growth is assessed according to the types of renewable energy sources. This impact assessment was implemented through the panel autoregressive distributed lag (ARDL) approach and causality analysis. Additionally, the Hausman test is conducted within the regression model [3].

The ARDL model has been employed to investigate the relationship between China's trade openness and economic growth. In the ARDL model, the volume of foreign direct investment, trade openness, and indicators of the real effective exchange rate were selected as independent variables, whereas the economic growth indicator was chosen as the dependent variable [4].

This study empirically investigates the nexus between financial intermediation development and economic growth in Nigeria, employing the autoregressive distributed lag (ARDL) approach within a cointegration analysis framework. The findings reveal that the relationship between financial development and economic growth in Nigeria does not significantly deviate from patterns observed in oil-dependent economies. Specifically, the association between financial intermediation development and economic growth in Nigeria is found to be insignificantly negative in the long run and significantly negative in the short run. The results underscore the pivotal role of the oil sector in Nigeria's economic activities [5].

The interdependence between CO₂ emissions, renewable energy consumption, and economic growth in Tunisia is evaluated using the Autoregressive Distributed Lag (ARDL) model. This study addresses the following questions: Does renewable energy utilization exert a positive impact on economic growth? Does renewable energy utilization result in a reduction in CO₂ emissions? Is CO₂ emissions correlated with economic growth? [6].

In this study, the impact of trade openness on economic growth in countries bordering the Mediterranean Sea is assessed using the ARDL-PMG approach. The results indicate that trade and financial openness variables contribute positively to economic growth. The free trade agreements signed by the European Union with selected countries in the Mediterranean basin are primarily designed to expand regional economic integration and enhance their potential growth [7].

This study investigates the relationships between economic growth, financial innovations, and stock market development in Bangladesh over the period from 1980 to 2016. The ARDL bounds testing approach is employed to examine long-run cointegration, alongside Granger causality tests. The research findings indicate that financial innovations and stock market development exhibit bidirectional causality with economic growth in both the long run and short run. This underscores the significance of market-based financial systems in regional economic development. In developing regions such as Bangladesh, supporting financial innovations may stimulate economic growth [8].

In his study, M. Ageli examines the interrelationships among health care expenditures, green energy, environmental sustainability, and economic growth in Saudi Arabia over the period from 1995 to 2021, employing the Bootstrap ARDL methodology. The research findings indicate the absence of long-term cointegration; however, a unidirectional causality exists between economic growth and health care expenditures, while a bidirectional causality is observed between CO₂ emissions and green energy. Furthermore, investments in health care and green energy are found to support economic stability in the context of regional development [9].

T.H. Nguyen et al. employ the Autoregressive Distributed Lag (ARDL) model in their empirical study to meticulously examine the multifaceted interdependencies among innovation, globalization, and productivity across a sample of 76 developed and

developing countries. The research applies rigorous econometric methods within the ARDL framework to ascertain the short- and long-term impacts of innovation and globalization on productivity levels. The findings underscore a robust and statistically significant relationship between innovation and productivity, as well as the positive effect of globalization on enhancing productivity. These results highlight the transformative potential of innovation and the facilitative role of globalization in promoting productivity growth [10].

2. Materials and Methods

Based on the results and insights derived from the aforementioned studies, in the present research, we employed autoregressive distributed lag (ARDL) models to assess the long-term and short-term impacts on the region's socio-economic development. Initially, the formation of this model necessitates the selection of dependent and independent variables. Accordingly, we selected the following factors as dependent and independent variables: the dependent variable (outcome factor) – gross regional product (GRP) per capita (in thousand soums) – (*GRP per capita*); the independent variables (influencing factors) – industrial production per capita (in thousand soums) – (*IP per capita*); fixed capital investments per capita (in thousand soums) – (*FCI per capita*); unemployment rate (in percent) – (*Unem Rate*).

To better interpret the multivariate econometric model that we intend to formulate, we apply the natural logarithm to all variable values.

To analyze the effects of the independent variables, we employ a linear model in the natural log-transformed form of all variables. This model can be represented as follows:

$$\text{LOG}(\text{GRP per capita})_t = a_0 + a_1\text{LOG}(\text{IP per capita})_t + a_2\text{LOG}(\text{FCI per capita})_t + a_3\text{LOG}(\text{Unem Rate})_t + \varepsilon_t \quad (1)$$

here: $\text{LOG}(\text{GRP per capita})$ – denotes the logarithm of gross regional product per capita, $\text{LOG}(\text{IP per capita})$ – represents the logarithm of industrial production volume per capita, $\text{LOG}(\text{FCI per capita})$ – indicates the logarithm of fixed capital investment assimilated per capita, $\text{LOG}(\text{Unem Rate})$ – signifies the logarithm of the unemployment rate, the subscript t corresponds to the time period spanning from 2005 to 2024, while a_0 is the intercept term, a_1, a_2, a_3 are the coefficients associated with the influencing factors, and ε_t represents the error term.

In this analysis, we employ the ARDL model developed by Pesaran and Shin [11]. Applying this model necessitates the implementation of the following steps:

- a. Stationarity testing: Assessing whether the time series are stationary or non-stationary using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests;
- b. Optimal lag length selection: Determining the optimal lag lengths for the dependent and independent variables, for example, through the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), or Hannan-Quinn (HQ) criteria;
- c. Model parameter estimation: Evaluating the short-run and long-run coefficients;
- d. Cointegration testing (long-term equilibrium relationship): Examining the presence of cointegration via the ARDL bounds test. If the F-statistic exceeds the critical values, cointegration is considered to exist;
- e. Model adequacy assessment: Analyzing the residuals for autocorrelation, heteroskedasticity, and normality.

It is noteworthy to emphasize at this juncture that the F-statistic is computed to test for the presence of cointegration. The F-statistic is evaluated based on the null hypothesis H_0 (no cointegration exists) and the alternative hypothesis H_1 (cointegration exists). Following the computation of the F-statistic, it is compared against the asymptotic critical value bounds provided by Pesaran, Shin, and Smith [12]. If the calculated F-statistic exceeds the upper bound, the H_1 hypothesis is accepted, indicating the presence of

cointegration. If the F-statistic falls below the lower bound, the H_0 hypothesis is accepted, signifying the absence of cointegration. If the F-statistic lies between the bounds, the outcome remains inconclusive.

If the null hypothesis H_0 is not rejected, the specification of the ARDL model represents solely the short-run estimation results and can be expressed as follows:

$$\begin{aligned} \Delta \text{LOG}(\text{GRP per capita})_t = & b_0 + \sum_{i=1}^{p-1} b_i \Delta \text{LOG}(\text{GRP per capita})_{t-i} + \\ & \sum_{j=0}^{q-1} c_j \Delta \text{LOG}(\text{IP per capita})_{t-j} + \sum_{j=0}^{q-1} d_j \Delta \text{LOG}(\text{FCI per capita})_{t-j} + \\ & \sum_{j=0}^{q-1} e_j \Delta \text{LOG}(\text{Unem Rate})_{t-j} + \alpha_1 \text{LOG}(\text{GRP per capita})_{t-1} + \alpha_2 \text{LOG}(\text{IP per capita})_{t-1} + \\ & \alpha_3 \text{LOG}(\text{FCI per capita})_{t-1} + \alpha_4 \text{LOG}(\text{Unem Rate})_{t-1} + \varepsilon_t \end{aligned} \quad (2)$$

Here, Δ denotes the first-order differencing of the variables, (b_0) represents the constant term, $(b_i), (c_j), (d_j), \text{and } (e_j)$ are the short-term dynamic impact coefficients, $(\alpha_1), (\alpha_2), (\alpha_3), \text{and } (\alpha_4)$ are the long-term dynamic multipliers, (n) is the length of the lag (time interval), (p) and (q) are the orders of the lags (delays), and (ε_t) is the error term.

It is well-established that, in the construction of multifactor econometric models, the Ljung-Box (Q) [13] test is initially employed to ascertain the presence or absence of autocorrelation in the time series data (for both dependent and independent variables involved in the model). The existence of autocorrelation in these time series necessitates an examination of their stationarity. Subsequently, to assess the stationarity of the variables and determine their order of integration, the Augmented Dickey-Fuller (ADF) [14] and Phillips-Perron (PP) [15] unit root tests are applied. Next, taking into account the potential existence of short-term and long-term ARDL model equations, it is essential to conduct the Bounds test to determine which formulation should be utilized. In the final stage, robustness tests are applied to the ARDL model developed specifically for this research endeavor.

3. Results and Discussion

The null hypothesis (H_0) of the Ljung-Box test (absence of autocorrelation in the time series) and the alternative hypothesis, namely H_1 (presence of autocorrelation in the time series), are regarded as the primary hypotheses. It is well-established that in this test, a p-value < 0.05 indicates rejection of H_0 in favor of H_1 , whereas a p-value > 0.05 indicates failure to reject H_0 [16]. The following table presents the results of the autocorrelation test conducted on the factors, see Table 1.

Table 1. Ljung-Box Test Results for dependent and independent variables.

LOG(GRP per capita)				
Lag	AC	PAC	Q-Stat	Prob
1	0.717	0.717	7.3455	0.007
2	0.448	-0.136	10.527	0.005
3	0.201	-0.138	11.248	0.010
4	0.002	-0.102	11.248	0.024
5	-0.163	-0.130	11.880	0.036
LOG(IP per capita)				
Lag	AC	PAC	Q-Stat	Prob
1	0.741	0.741	7.8438	0.005
2	0.466	-0.182	11.299	0.004
3	0.200	-0.169	12.012	0.007
4	-0.018	-0.107	12.019	0.017
5	-0.170	-0.075	12.704	0.026
LOG (FCI per capita)				
Lag	AC	PAC	Q-Stat	Prob
1	0.669	0.669	6.3979	0.011
2	0.338	-0.198	8.2117	0.016

3	0.091	-0.089	8.3602	0.039
4	-0.018	0.024	8.3670	0.079
5	-0.040	0.011	8.4058	0.135
LOG(Unem Rate)				
Lag	AC	PAC	Q-Stat	Prob
1	0.615	0.615	5.4053	0.020
2	0.351	-0.044	7.3591	0.025
3	-0.059	-0.414	7.4217	0.060
4	-0.119	0.185	7.7095	0.103
5	-0.177	-0.023	8.4575	0.133

Source: Author estimations

From the data presented in the aforementioned table, it is evident that autocorrelation is present in all variables. In the subsequent stage of examining the variables for stationarity, the Augmented Dickey-Fuller (ADF) unit root test holds significant importance. The results of the stationarity tests for the variables are provided in the following table, see Table 2.

Table 2. Results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit Root Tests for Stationarity of Dependent and Independent Variables.

	Augmented Dickey-Fuller (ADF)				(Order of integration)
	(Levels)	(Probability)	(1st differences)	(Probability)	
LOG(GRP per capita)	-1.74	0.38	-4.27	0.00	I (1)
LOG(IP per capita)	-0.98	0.73	-3.44	0.02	I (1)
LOG(FCI per capita)	-0.66	0.82	-3.92	0.01	I (1)
LOG(Unem Rate)	-0.95	0.73	-3.89	0.01	I (1)
	Phillips-Perron (PP)				(Order of integration)
	(Levels)	(Probability)	(1st differences)	(Probability)	
LOG(GRP per capita)	-4.17	0.00	-4.61	0.00	I (1)
LOG(IP per capita)	-1.23	0.62	-3.43	0.02	I (1)
LOG(FCI per capita)	-0.66	0.82	-3.92	0.01	I (1)
LOG(Unem Rate)	-1.81	0.35	-3.25	0.04	I (1)

Source: Author estimations

According to Table 2 above, the variables representing per capita gross regional product (GRP) volume, per capita investments allocated to fixed capital, per capita industrial output, and the unemployment rate are all stationary after first-order differencing. Therefore, the order of integration for all these variables is adopted as I(1). In the subsequent stage, it is necessary to select the optimal lag order (time interval) for the variables included in the model. To this end, the optimal lag order from the vector autoregressive (VAR) model is employed, see Table 3.

Table 3. Determination of the Lag Order for Autoregressive Distributed Lag (ARDL) Models.

Lag	AIC	SC (BIC)	HQ
0	-2.849477	-2.728443	-2.982251
1	-10.92429*	-10.31912*	-11.58816*
2	-8.324356	-7.546321	-5.345219
3	-9.765435	-6.876592	-8.657894

Source: Author estimations

Based on the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ) presented in Table 3 above, the lag order for the autoregressive distributed lag (ARDL) model can be determined to be 1. This is because the values computed for lag 1 across all these criteria are the smallest relative to those calculated for the remaining lags.

Before identifying long-run and short-run relationships among variables, it is essential to confirm the existence of cointegration. This is achieved through the application of the ARDL Bounds Test. As is well-established, in the ARDL Bounds Test, if the F-statistic exceeds the upper bound of the asymptotic critical values, it signifies the presence of cointegration; if the F-statistic falls between the upper bound and lower bound of the asymptotic critical values, the evidence for cointegration is inconclusive; and if the F-statistic is below the lower bound of the asymptotic critical values, it indicates the absence of cointegration. The results of the ARDL Bounds Test are presented in the following Table 4.

Table 4. Results of the ARDL Bounds Test.

(Test Statistic)	(Value)	(Significant)	(Lower bound)	(Upper bound)
			I (0)	I (1)
F-statistic	47.47827	10%	2.37	3.2
		5%	2.79	3.67
		2.5%	3.15	4.08
		1%	3.65	4.66

Source: Author estimations

As can be seen from Table 4 above, the F-statistic value exceeds the asymptotic critical values' "Lower bound" and "Upper bound" at all significance levels. This situation indicates the presence of cointegration and the feasibility of formulating long-run and short-run equations, see Table 5.

Table 5. Estimation Results for Parameters Representing Long-Term and Short-Term Effects Based on the ARDL (1, 1, 1, 1) Model.

Dependent Variable: <i>LOG(GRP per capita)</i>				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long – run				
<i>LOG (GRP per capita) (-1)</i>	-0,918294	0,322159	-2,85044	0.01724
<i>LOG (IP per capita)</i>	2,213942	0,054102	40,92163	0.00000
<i>LOG (IP per capita) (-1)</i>	1,653399	0,224632	7,360478	0.00002
<i>LOG (FCI per capita)</i>	5,294021	0,099146	53,39621	0.00000
<i>LOG (FCI per capita) (-1)</i>	1,122167	0,030158	37,2096	0.00000
<i>LOG (Unem Rate)</i>	-1,184828	0,087432	-13,5514	0.00000
<i>LOG (Unem Rate) (-1)</i>	-1,427878	0,111515	-12,8044	0.00000
<i>Constant</i>	5,034632	1,020487	4,933558	0.00059
Short – run				
<i>D LOG (IP per capita)</i>	1,213942	0.021057	57,65028	0.00000
<i>D LOG (FCI per capita)</i>	2,294021	0.015766	145,5043	0.00000
<i>D LOG (Unem Rate)</i>	-1,154828	0.016603	-69,5554	0.00000

<i>ECM</i> (-1)	-1,418294	0.053146	-26,6867	0.00000
Diagnostics/stability				
Ramsey RESET Test				0.82
Breusch-Godfrey Serial Correlation LM Test				0.67

Source: Author estimations. For RESET and Breusch-Godfrey Serial Correlation LM tests, p-values are reported. The null hypothesis in the RESET test is that there is no equation specification error, while for the Breusch-Godfrey Serial Correlation LM test, the null hypothesis is that there is no serial correlation.

The empirical results of the estimated long-term effects (Table 5) indicate that a 1% increase in per capita industrial output volume may lead to a 3.9% increase in per capita GRP, a 1% rise in per capita investments assimilated into fixed capital may result in a 6.9% increase in per capita GRP, and furthermore, a 1% elevation in the unemployment rate may cause a 2.6% decrease in per capita GRP.

The empirical results of the estimated short-term effects indicate that a 1% increase in per capita industrial output volume may lead to a 1.21% rise in per capita gross regional product (GRP), a 1% increase in per capita investments assimilated into fixed capital may result in a 2.3% increase in per capita GRP, and furthermore, a 1% rise in the unemployment rate may cause a 1.15% decrease in per capita GRP.

The *ECM*(-1) (Error Correction Mechanism) [17] indicates the speed of adjustment toward long-term equilibrium following short-term negative impacts. It explains that deviations from short-term equilibrium, associated with per capita GRP volume, per capita industrial output, per capita investments allocated to fixed capital, and unemployment rate indicators, can result in an annual adjustment of 1.41 percent decrease or increase in the long term. Additionally, the RESET (regression equation specification error test) coefficient (0.82) provides evidence that the model is adequate and free from specification errors. The Breusch-Godfrey Serial Correlation LM test coefficient (0.67) suggests that there is no autocorrelation in the estimated ARDL model.

4. Conclusion

The analyses conducted in the present research study have enabled the formulation of the following conclusions. In particular:

- a. It has been established that long-term and short-term relationships exist with the indicators of per capita gross regional product (GRP) volume, per capita industrial output, per capita investments assimilated into fixed capital, and the unemployment rate.
- b. The empirical results of the estimated short-term effects indicate that a 1% increase in per capita industrial output volume can lead to a 1.21% rise in per capita GRP, a 1% increase in the volume of investments assimilated into fixed capital per capita can result in a 2.3% increase in per capita GRP, and furthermore, a 1% rise in the unemployment rate may cause a 1.15% decrease in per capita GRP.
- c. The empirical findings from the estimated long-term effects indicate that a 1% increase in per capita industrial output volume may result in a 3.9% rise in per capita GRP; a 1% increase in per capita investment assimilated into fixed capital may lead to a 6.9% increase in per capita GRP; moreover, a 1% rise in the unemployment rate could cause a 2.6% decline in per capita GRP.

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