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Linking Governance Quality to Smart City Performance in Algeria: A Multidimensional Analysis

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Abstract:

The concept of the smart city represents an integrated approach that combines technology, governance, and citizen participation to enhance urban sustainability and quality of life. Governance plays a crucial role in the success of smart cities by ensuring transparency, accountability, and inclusive decision-making through institutional, regulatory, and participatory mechanisms. Empirical studies highlight governance as a key driver of innovation, sustainability, and competitiveness in major cities. However, despite the global rise of smart city initiatives, performance disparities persist. This underscores the importance of assessing governance quality through composite indicators to better understand its impact on the overall success of smart cities.

Keywords: smart city, technology, governance, performance, infrastructure.

JEL Classification: O18 ; O33 ; H11, L25, H54

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Introduction

The smart city concept offers an integrated response to contemporary urban challenges by combining technological innovation, environmental sustainability, and citizen participation. A smart city does not limit itself to the use of information and communication technologies; it incorporates several interdependent dimensions, such as smart mobility, open governance, sustainable resource management, economic innovation, and quality of life (Kourtit, Nijkamp, & Arribas, 2012). Frameworks such as the IESE Cities in Motion Index (Berrone, Ricart, & Carrasco, 2020) and ISO 37120/37122 standards bring these dimensions together into measurable pillars, whose overall performance depends on the synergy among them.

Governance plays a transversal role that is essential to the success of smart cities. It refers to the set of institutional, regulatory, and participatory mechanisms that guide and coordinate public action. In smart city development, governance often emerges in the form of what the literature refers to as “smart governance.” (Pereira, Macadar, Luciano, & Testa, 2017). This approach emphasizes transparency and open data, citizen participation, multi-actor coordination among the public sector, private sector, and civil society, and efficient administrative processes. According to(Meijer & Bolívar, 2016), without adequate governance, technological investments may not translate into tangible urban performance gains, while (Gil-Garcia, Zhang, & Puron-Cid, 2016) highlight the critical role of the digital dimension in steering smart city projects.

Empirical research confirms governance’s central role in smart city performance. For example,(Kourtit, Nijkamp, & Arribas, 2012) show that Europe’s top-performing cities in innovation and sustainability enjoy strong institutional frameworks.In the same vein(Gil-Garcia, Pardo, & Nam, 2015)demonstrate that governance acts as a catalyst by creating an environment favorable to technological investment and public-private partnerships. Similarly, (Berrone, Ricart, & Carrasco, 2020), through the IESE Cities in Motion Index, identify governance as a determinant of global urban competitiveness. Bolívar and Meijer (2016) link governance to composite indicators of urban performance and illustrate the value of methods such as Principal Component Analysis (PCA) in summarizing the multiple dimensions of a smart city.

Despite the rise of smart city initiatives worldwide, performance gaps remain significant, even among territories with similar economic and technological levels. This disparity raises a key question: to what extent does governance quality influence overall smart city performance? Addressing this question requires constructing a composite indicator that captures the various dimensions of a smart city and then examining its relationship with established governance measures.

This research builds a composite Smart City Performance Score using indicator from the World Development Indicators (WDI) database of the World Bank. The data cover key dimensions such as environment and energy (CO emissions per capita, renewable energy share, waste management), digital and innovation (internet penetration, mobile subscriptions, R&D investment), mobility and infrastructure (public transport network length, electricity access, road quality), and quality of life (access to safe water, life expectancy, urban safety). After standardizing the data, a PCA will reduce dimensionality and produce a score that maximizes explained variance.

This score will serve as the dependent variable in an econometric model where one or more dimensions from the World Governance Indicators (WGI) — such as government effectiveness, regulatory quality, control of corruption, rule of law, political stability, and voice and accountability — may be included as the main explanatory variables, depending on their relevance and statistical significance. Control variables such as GDP per capita, urbanization rate, total population, and public investment spending will help isolate governance's specific effect. This approach tests the hypothesis that strong governance enhances smart city performance, all else being equal, and provides empirical evidence on the institutional drivers of intelligent urban development.

Accordingly, the study advances two hypotheses:

- H1: Strong governance — reflected in government effectiveness, regulatory quality, and rule of law — is positively associated with higher Smart City Performance Scores.
- H2: The effect of governance on smart city performance remains significant after controlling for economic and demographic factors, indicating that governance exerts an independent influence.

Methodology

1. Data and Variables

This study relies on an annual dataset covering the period 2000–2022 for Algeria, compiled from multiple internationally recognized sources. The data were collected from the World Development Indicators (WDI) of the World Bank, the International Telecommunication Union (ITU), the Emissions Database for Global Atmospheric Research (EDGAR), and the FAO AQUASTAT database. These sources were selected due to their methodological consistency, international comparability, and availability of long historical series.

The selected indicators capture three core dimensions of smart city performance — planet, infrastructure, and digitalization — which align with global frameworks such as the United Nations Sustainable Development Goals (SDGs) and the European Smart City Model.

- **Planet (Environmental Performance):** This dimension measures the ecological sustainability of urban development and the environmental pressures associated with economic activity.
- **Total greenhouse gas emissions ($MtCO_2$ e):** Captures the overall contribution of Algeria to global climate change and serves as a proxy for environmental impact of energy consumption and production.
- **Level of water stress (percentage of freshwater resources):**Measures the proportion of total freshwater withdrawn relative to available renewable resources, reflecting the sustainability of water use and potential risks for urban supply systems.
- **Infrastructure (Urban and Mobility Performance):**This dimension reflects the quality of physical infrastructure and the environmental consequences of mobility.
- **GHG emissions from the transportation sector ($MtCO_2$ e):** Indicates the carbon intensity of transport systems, a critical factor in urban sustainability.
- **Urban population (percentage of total population):**Represents the share of the population living in urban areas, highlighting demographic pressures on infrastructure, services, and governance.
- **Digital (Technological Performance):** This dimension assesses Algeria’s progress in adopting digital technologies and fostering innovation.

- **Percentage of individuals using the Internet (%):** Serves as a proxy for digital inclusion, innovation potential, and the degree of citizen connectivity, which are central elements of smart city development.

2. Composite Smart City Performance Score (SCPS)

To capture the multidimensional nature of urban performance, these indicators will be integrated into a single index — the Smart City Performance Score (SCPS) — through Principal Component Analysis (PCA). This method reduces dimensionality while retaining the maximum variance of the dataset, allowing for the construction of an objective, data-driven index that balances environmental, infrastructural, and digital dimensions.

3. Principal Component Analysis (PCA)

The construction of the Smart City Performance Score (SCPS) relies on Principal Component Analysis (PCA), a multivariate statistical technique that reduces data dimensionality while preserving as much information as possible. PCA is particularly suited for this research because it aggregates multiple correlated indicators into a single synthetic index, thereby allowing a more coherent measurement of smart city performance.

3.1. Pre-processing of Data

Before applying PCA, all raw indicators were transformed into standardized values (z-scores). This step was necessary to eliminate scale effects, since the variables are expressed in different units (e.g., percentages, megatonnes of CO_2 -equivalent, population shares). Standardization ensures that each variable contributes equally to the analysis and that results are not biased toward indicators with larger numerical ranges.

3.2. Dimensionality Reduction

The standardized dataset was subjected to PCA using the variance–covariance structure. The eigenvalues associated with each principal component were examined to determine the number of components to retain. The Kaiser criterion (eigenvalues > 1) and the scree plot were used to guide selection. In line with standard practice, the first principal component (PC1) — which captures the largest share of the total variance — was selected as the most representative dimension of smart city performance.

3.3. Interpretation of Loadings

The component loadings, which represent the correlation between each original variable and the extracted component, were analyzed to assess the contribution of each indicator to the Smart City Performance Score. Higher absolute loadings indicate a stronger influence of that indicator on the composite score. This interpretation step is crucial for validating that the constructed index meaningfully combines environmental, infrastructural, and digital dimensions.

3.4. Construction of the Smart City Performance Score (SCPS)

The Smart City Performance Score (SCPS) was computed as the linear combination of the standardized variables weighted by their PCA loadings on PC1. Formally:

$$SPCS_t = W_1 Z_{1t} + W_2 Z_{2t} + \cdots W_n Z_{nt}$$

Where Z_{it}represents the standardized value of indicator$i$in year$t$, and $W_i$is the PCA loading of indicator $i$on PC1.

3.5. Use in Econometric Modeling

The resulting SCPS time series (2000–2022) serves as the dependent variable in the subsequent econometric analysis. It captures a synthetic measure of Algeria's smart city performance over time, integrating environmental sustainability, infrastructure quality, and digitalization. This allows testing the impact of governance quality and control variables on overall smart city performance in a rigorous, quantitative manner.

4. Econometric Strategy

The econometric strategy is designed to rigorously examine the relationship between governance quality and Algeria's Smart City Performance Score (SCPS), while addressing the time-series properties of the data. The methodological steps include testing for stationarity, assessing cointegration, and specifying the appropriate regression framework.

4.1. Stationarity Testing

Time-series data often exhibit non-stationarity, which can lead to spurious regression results if not properly addressed. To ensure valid inference, the Phillips–Perron (PP) test is applied to each variable.

Variables that are stationary in levels (I(0)) are included in their original form.

Variables that are stationary only after first differencing (I(1)) are transformed accordingly.

Variables found to be integrated of order two (I(2)), if any, will be excluded from the analysis, since they are incompatible with standard econometric frameworks such as ARDL and Johansen cointegration.

This step ensures that the dataset is consistently structured for subsequent modeling.

4.2. Cointegration Analysis

Cointegration tests assess whether SCPS and its variables share a stable long-run relationship. If variables show mixed integration orders (I(0) and I(1)), the ARDL bounds test will be used, suitable for small samples. If all variables are I(1), the Johansen test applies, justifying a VECM model. Without cointegration, models in first differences ensure stationarity.

This dual approach allows the econometric framework to adapt to the specific data properties of the Algerian case.

4.3. Regression Framework

The general empirical model is specified as:

$$\mathrm{SCPSt} = \alpha + \beta 1\mathrm{GOVt} + \beta 2\mathrm{ECONt} + \beta 3\mathrm{DEMOt} + \varepsilon \mathrm{t}$$

Where:

- $\boldsymbol{SCPS}$**:** Smart City Performance Score, derived from PCA.
- $\boldsymbol{GOV}$**:**Governanceindicators
- $\boldsymbol{ECON}$**:** Economic controls (GDP per capita, public investment spending).
- $\boldsymbol{DEMO}$**:**Demographic controls (urbanization rate, population size).

The final model specification will depend on the outcomes of the stationarity and cointegration tests:

- OLS regression if all variables are stationary in levels.
- ARDL framework if the variables are of mixed integration orders ($(I(0)/I(1))$) and cointegration exists.
- VECM specification if all variables are I(1) and cointegrated.
- Differenced regression models if no long-run cointegrationis detected.

This flexible econometric design ensures that the analysis captures both short-term fluctuations and long-term dynamics in the relationship between governance and smart city performance in Algeria.

Result:

1. Principal component results

1.1. Eigenvalues and Variance Explained

Table 1. Principal Component Results: Eigenvalues and Variance Explained

Component	Eigenvalue	Proportion of Variance (%)	Cumulative Proportion of Variance (%)
PC1	5.45	90.86%	90.86%
PC2	0.38	6.36%	97.22%
PC3	0.09	1.50%	98.72%
PC4	0.06	0.97%	99.69%
PC5	0.01	0.23%	99.92%

Source: Author's calculations using EViews software.

Table 1 presents the eigenvalues and the percentage of variance explained by each principal component. The results clearly show that the first component (PC1) has an eigenvalue of 5.45, which exceeds the threshold of 1 and accounts for 90.86% of the total variance. This proportion is remarkably high, indicating that a single dimension is sufficient to summarize the information contained in the six original indicators. The subsequent components explain only marginal portions of variance, with PC2 adding 6.36% and all others contributing less than 2% each. Based on Kaiser's criterion and the cumulative variance rule, PC1 alone captures nearly the entire variability of the dataset, justifying its use as the Smart City Performance Score (SCPS).

1.2. Component Loadings for PC 1

Table 2 presents the factor loadings of the six indicators on the first principal component.

Table 2. Component Loadings for Principal Component 1 (PC1)

Variable	Loading on PC1
GHG_TOTAL	0.423
WaterStress_Level	-0.373
GHG_TRANSPORT	0.414
Pop_UrbanPct	0.426
Elec_AccessPct	0.402
Internet_UsePct	0.409

Source: Author's calculations using EViews software.

All variables, except water stress, load positively and strongly on PC1, with coefficients ranging from 0.402 (electricity access) to 0.426 (urban population share). The negative loading of water stress (–0.373) indicates that lower levels of water scarcity are associated with higher composite scores. This component can therefore be interpreted as a "General Development and Environmental Impact" axis, capturing the joint dynamics of urbanization, technological adoption, infrastructure access, and environmental pressures. High PC1 scores correspond to contexts with greater urban concentration, higher connectivity (internet penetration and electricity access), and higher emissions from both total and transport-related sources, combined with relatively lower water stress. In sum, PC1 effectively distinguishes advanced, urbanized, and digitally integrated economies from less developed settings.

2. Stationarity results

Table 3: Phillips–Perron (PP) Stationarity Test Results

Model	**Model 1: With Trend and Constant**		**Model 2: Without Trend but With Constant**		**Model 3: Without Trend and Without Constant**	
	I(0)	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
PC1_score	0.4136	0.0118	0.9608	0.0019	0.4633	0.0589
CC	0.0023	0.0000	0.0004	0.0000	0.6342	0.0000
GE	0.0002	0.0000	0.0001	0.0001	0.4205	0.0000
RQ	0.7115	0.0064	0.6431	0.0010	0.3754	0.0000
RL	0.0081	0.0078	0.0300	0.0006	0.6409	0.0000
SPAV	0.2206	0.0009	0. 1813	0.0001	0.8331	0.0000
VA	0.4552	0.1589	0.1785	0.0496	0.7071	0.0038
HDI	0.0000	0.0000	0.0000	0.0024	1.0000	0.0024
GDP_def	0.0083	0.0000	0.0936	0.0000	0.2468	0.0000
POP_r	0.9967	0.0357	0.5670	0.0394	0.7256	0.0029

Source: Author's calculations using EViews software.

Table 3 reports the Phillips–Perron (PP) unit root tests applied to all variables under three model specifications (with trend and constant, with constant only, and without trend or constant). The Smart City Performance Score (PC1) is found to be non-stationary at levels but becomes stationary after first differencing, confirming an order of integration I(1). Several governance indicators, such as Control of Corruption (CC) and Government Effectiveness (GE), are stationary in levels (I(0)), while Regulatory Quality (RQ), Voice and Accountability (VA), and Stability and Absence of Violence (SPAV) are integrated of order one (I(1)). Rule of Law (RL) shows mixed evidence but is largely consistent with stationarity in levels. Regarding control variables, both GDP per capita (GDP_def) and population growth (POP_r) are I(1). These results indicate a mixture of I(0) and I(1) series, justifying the use of an ARDL bounds testing approach to explore potential long-run cointegration relationships among the variables.

3. Cointegration results

Table 4. ARDL Bounds Test for Cointegration

Test Statistic	Significance	I(0) Bound	I(1) Bound
94.70	10%	1.85	2.85
	5%	2.11	3.15
	2.5%	2.33	3.42
	1%	2.62	3.77

Source: Author's calculations using EViews software.

Table 4 presents the results of the ARDL bounds test. The calculated F-statistic of 94.70 exceeds the upper critical values at all conventional significance levels, including the 1% threshold (3.77). This provides overwhelming evidence to reject the null hypothesis of no cointegration. The results confirm the existence of a stable long-run equilibrium relationship between the Smart City Performance Score (PC1) and the explanatory variables, namely the governance indicators (CC, GE, RL, RQ, SPAV, VA), along with the economic and demographic controls (GDP_defl, POP_r). Consequently, an Error Correction Model (ECM) framework is appropriate to capture both the short-run dynamics and the long-run adjustment process driving smart city performance in Algeria.

4. ARDL-ECM Regression Results

1.3. Identification of the optimal lag

The optimal lag structure balances dynamic accuracy with model simplicity. Based on the AIC and Schwarz Bayesian Criterion (SBC), the study identifies the optimal lag configuration as (1,1,1,1,1,1,1,1,1), which assigns one lag to all the variables.

1.4. Long-Run Equation

The long-run equation describes the stable, equilibrium relationship between the variables.

Table 5. ARDL-ECM Long-Run Estimates

Variable	Coefficient	Std. Error	t-Statistic	p-value
CC	-0.0942	0.0270	-3.485	0.0734
GE	-0.0963	0.0181	-5.309	0.0337
RL	0.1103	0.0179	6.164	0.0253
RQ	-0.2219	0.0150	-14.768	0.0046
SPAV	0.2150	0.0184	11.665	0.0073
VA	0.2395	0.0212	11.311	0.0077
GDP_DEFL	0.0078	0.0056	1.392	0.2986
POP_R	-2.4476	0.5589	-4.379	0.0484
C (Constant)	4.6727	1.0565	4.423	0.0475

Source: Author’s calculations using EViews software.

Table 5 reports the long-run coefficients of the ARDL-ECM model. The results reveal significant governance, economic, and demographic effects on Algeria’s Smart City Performance Score (SCPS). Among governance indicators, the rule of law (RL), stability of policies and regulations (SPAV), and voice and accountability (VA) exert strong positive and statistically significant effects, suggesting that institutional quality and citizen participation are critical drivers of smart city development. By contrast, regulatory quality (RQ) and government effectiveness (GE) display significant negative associations, implying that perceived inefficiencies or overly restrictive regulatory environments may constrain smart city progress. Control of corruption (CC) also enters with a negative coefficient, though its statistical significance is weaker.

4.3.**Short-Run Dynamics (ECM Regression)**

Table 6 presents the short-run dynamics of the ARDL-ECM model. Several governance indicators exert immediate and statistically significant effects on Algeria’s Smart City.

Table 6. ARDL-ECM Short-Run Dynamics

Variable	Coefficient	Std. Error	t-Statistic	p-value
D(CC)	-0.0835	0.0021	-39.70	0.0006
D(GE)	-0.0520	0.0019	-27.41	0.0013
D(RL)	0.0225	0.0017	13.35	0.0056
D(RQ)	-0.0554	0.0020	-28.18	0.0013
D(SPAV)	0.1205	0.0023	51.45	0.0004
D(VA)	-0.0168	0.0037	-4.58	0.0446
D(GDP_DEFL)	0.0132	0.0006	23.37	0.0018
D(POP_R)	1.0698	0.0747	14.33	0.0048
Error Correction Term)	-0.6935	0.009610	0.009610	0.0000
R-squared		0.8951		

Source: Author's calculations using EViews software.

Performance Score (SCPS). Control of corruption (D(CC)) and government effectiveness (D(GE)) both display negative short-run impacts, suggesting that reforms in these domains may initially generate adjustment costs before benefits materialize. Regulatory quality (D(RQ)) also shows a significant negative short-run effect, reinforcing the notion of transitional frictions when regulatory frameworks shift.

Conversely, the rule of law (D(RL)) and policy stability (D(SPAV)) contribute positively in the short run, highlighting that legal certainty and predictable governance structures rapidly enhance smart city outcomes. Voice and accountability (D(VA)) surprisingly exhibits a small but significant negative coefficient, possibly reflecting short-term tensions linked to citizen demands or participation dynamics.

Among the control variables, GDP deflator (D(GDP_DEFL)) positively influences SCPS, suggesting that price adjustments are associated with improved performance, while demographic pressures (D(POP_R)) strongly enhance smart city outcomes, indicating that population dynamics and urban expansion are immediate drivers of development.

Finally, the highly significant and negative error correction term (–0.6935) confirms that nearly 69% of deviations from long-run equilibrium are corrected each year. This strong adjustment speed validates the existence of a stable long-run relationship between governance, economic, and demographic factors and Algeria’s smart city performance.

4.4.Model Confirmation and Diagnostic Tests

After establishing the existence of a long-run cointegrating relationship and estimating both the short-run and long-run dynamics through the ARDL-ECM framework, it is essential toverify the reliability of the estimated model. Diagnostic tests are therefore conducted to examine whether the residuals satisfy the key econometric assumptions. Specifically, we test for the presence of serial correlation, heteroskedasticity, and non-normality of residuals, as well as assess the overall stability of the model’s coefficients over time.

The confirmation process is critical because even if the estimated coefficients appear statistically significant, violations of these assumptions may undermine the validity of inference. To address this, we employ the Breusch–Godfrey LM test for autocorrelation, the White test for heteroskedasticity, and the Jarque–Bera test for normality. Furthermore, the stability of the model is evaluated using the CUSUM and CUSUMSQ tests. The results of these diagnostic procedures are presented in the following subsections.

Table 7. Breusch–Godfrey LM Test for

AutocorrelationBreusch-Godfrey LM test for autocorrelation	**p-value**
	0.5362

Source: Author’s calculations using EViews software.

The Breusch–Godfrey LM test yields a p-value of 0.5362, which is well above the 5% significance threshold. This means we fail to reject the null hypothesis of no serial correlation. Therefore, the residuals of the ARDL-ECM model are free from autocorrelation, confirming the reliability of the dynamic specification.

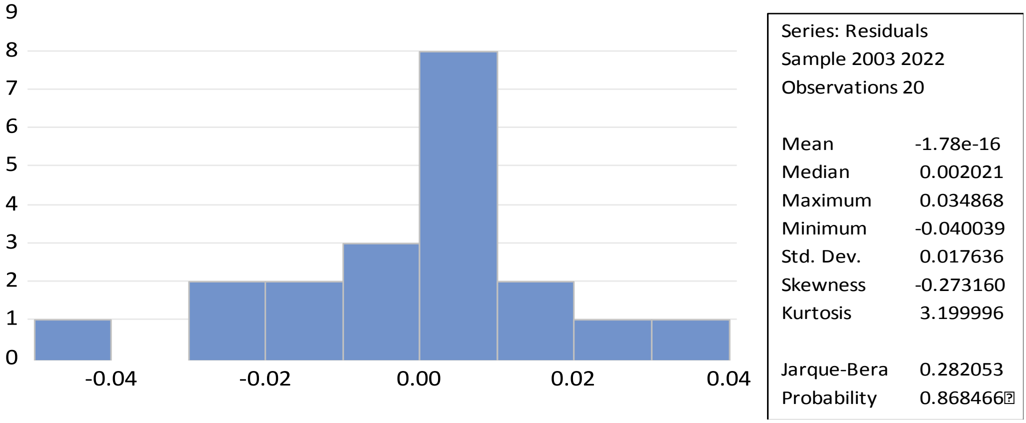
Table 8. White Test for Heteroskedasticity

White test for heteroscedasticity	p-value
	0.9563

Source: Author's calculations using EViews software.

The White test for heteroskedasticity produces a p-value of 0.9563, far above the 5% threshold. Thus, the null hypothesis of homoscedastic residuals cannot be rejected. This indicates that the variance of the residuals is constant, and the model does not suffer from heteroskedasticity problems.

Fig.2. Residuals Histogram and Descriptive Statistics



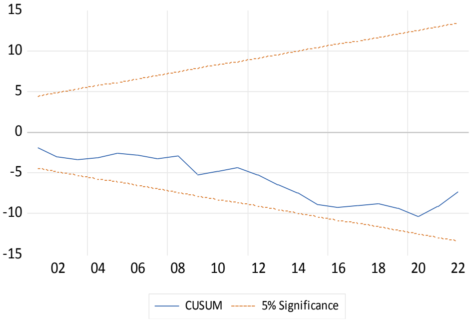
```
Series: Residuals
Sample 2003 2022
Observations 20

Mean          -1.78e-16
Median         0.002021
Maximum        0.034868
Minimum       -0.040039
Std. Dev.      0.017636
Skewness      -0.273160
Kurtosis       3.199996

Jarque-Bera    0.282053
Probability    0.868466
```

Source: Author's calculations using EViews software.

The results show that the Jarque–Bera statistic equals 0.1043483, with a p-value of 0.593499, which is far above the 5% threshold. We therefore do not reject the null hypothesis of normality. This finding confirms that the residuals follow a normal distribution, meeting one of the key validity requirements for econometric models.

After ensuring that the residuals are well-behaved in terms of serial correlation, variance, and distribution, we proceed to assess the stability of the estimated parameters. For this purpose, we apply the CUSUM and CUSUMSQ tests, which allow us to determine whether the model's coefficients remain stable over time.

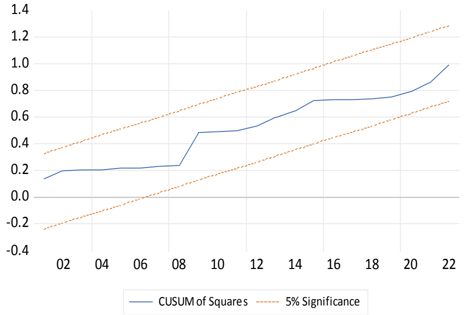
Fig.3.CUSUM Test for Stability of Coefficients



Source: Author's calculations using EViews software.

Fig.4.CUSUMSQ Test for Stability

of Coefficients



Source: Author's calculations using EViews software.

The results show that both the CUSUM and CUSUMSQ curves remain within the 5% critical bounds, confirming that the model's coefficients are stable over time. This ensures the robustness of the long run and short-run dynamics estimated by the ARDL-ECM model.

Discussion

1. Long-Run Dynamics

The long-run relationship is formally expressed by the estimated cointegration equation:

$$\begin{aligned} EC = PC1\_SCORE - (&-0.0942 * CC - 0.0963 * GE + 0.1103 * RL \\ &- 0.2219 * RQ + 0.2150 * SPAV + 0.2395 * VA \\ &+ 0.0078 * GDP\_DEFL - 2.4476 * POP\_R + 4.6727) \end{aligned}$$

This equilibrium equation illustrates how governance, macroeconomic, and demographic factors influence the Smart City Performance Score (SCPS) over the long run. Governance indicators show mixed effects: Control of Corruption (CC) with a negative coefficient (–0.0942), Government Effectiveness (GE) (–0.0963), and Regulatory Quality (RQ) (–0.2219) suggest that formal improvements may not immediately enhance smart city performance, consistent with (Gil-Garcia, Zhang, & Puron-Cid, 2016) who highlight challenges like coordination and institutional inertia. In contrast, Rule of Law (RL) (+0.1103), Stability and Absence of Violence (SPAV) (+0.2150), and Voice and Accountability (VA) (+0.2395) have strong positive impacts, supporting (Meijer & Bolívar, 2016) on the importance of legitimacy, trust, and participatory governance. Regarding control variables, GDP Deflator (GDPDEFL) has a small, insignificant effect (+0.0078), while population growth (POPR) has a large negative impact (–2.4476), echoing (Berrone, Ricart, & Carrasco, 2020) on demographic pressures undermining urban sustainability. The constant (+4.6727) represents the baseline SCPS level. Overall, governance quality is central to smart city performance, with effects varying across dimensions.

2. Short-Run Dynamics

The short-run adjustment dynamics are presented in the ARDL-ECM results (Table 6). Differenced governance variables show that Control of Corruption (D(CC)) has a significant negative short-term effect (–0.0835, $p < 0.01$), suggesting that sudden anti-corruption efforts disrupt informal networks before long-term benefits, aligning with (Gil-Garcia, Pardo, & Nam, 2015) on early resistance to governance innovation. Government Effectiveness (D(GE)) (–0.0520, $p < 0.01$) and Regulatory Quality (D(RQ)) (–0.0554, $p < 0.01$) also negatively affect SCPS short term, reflecting implementation frictions. Conversely, Rule of Law (D(RL)) (+0.0225, $p < 0.01$) and Stability and Absence of Violence (D(SPAV)) (+0.1205, $p < 0.01$) positively influence SCPS, showing short-term legal and political stability benefits. Voice and Accountability (D(VA)) has a small negative effect (–0.0168, $p < 0.05$), indicating that participatory processes may slow decision-making initially, consistent with (Meijer & Bolívar, 2016). Among controls, GDP Deflator (D(GDPDEFL)) has a small positive effect (+0.0132, $p < 0.01$), and population growth (D(POPR)) shows a large positive short-term impact (+1.0698, $p < 0.01$), contrasting with its negative long-term effect and reflecting demographic-driven demand and innovation (Berrone, Ricart, & Carrasco, 2020). The Error Correction Term (ECT) is strongly negative (–0.6935, $p < 0.01$), indicating rapid adjustment (about 69% correction per period) toward long-run equilibrium. Overall, short-run dynamics reveal immediate but sometimes opposing effects of governance reforms and demographic shifts on smart city performance

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