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DETERMINANTS OF CONSTRUCTION SECTOR GROWTH IN INDIA: THE ROLE OF INFRASTRUCTURE AND INFLATION

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Abstract

The construction sector plays a central role in infrastructure development and economic growth in India, yet empirical evidence on its macroeconomic drivers remains limited. This study examines the long-run and short-run relationships between infrastructure activity, inflation, and construction sector output using quarterly data from 2015–2025. A log-linear econometric framework is employed, incorporating Augmented Dickey–Fuller unit root tests, Johansen cointegration analysis, and an Autoregressive Distributed Lag (ARDL) model to capture dynamic adjustments. The results reveal that infrastructure expansion exerts a strong and statistically significant positive impact on construction sector GDP, underscoring its structural importance in driving sectoral growth. Inflation exhibits a negative but statistically insignificant effect in the long run. Diagnostic tests confirm model stability, with no evidence of autocorrelation or heteroskedasticity. The findings provide empirical support for infrastructure-led growth dynamics within an emerging economy context and highlight the importance of sustained infrastructure investment for stabilizing construction sector performance. Future research may extend the analysis through nonlinear modelling approaches or multi-country panel investigations.

Keywords: Construction Sector Growth; Infrastructure Investment; Inflation; ARDL Model; Cointegration; Sectoral Growth

1. Introduction

The construction sector plays a pivotal role in the economic transformation of emerging economies by facilitating infrastructure expansion, urbanisation, and capital formation. Across the Asia–Pacific region, rapid industrialisation and public investment programmes have strengthened the link between infrastructure development and macroeconomic growth, positioning construction activity as a key transmission channel between policy initiatives and real economic performance. In India, large-scale investments in transportation networks, energy systems, and urban infrastructure have contributed to sustained growth in construction output, reinforcing the sector's importance within the broader development framework. As infrastructure spending increasingly shapes long-run economic trajectories, understanding the macroeconomic determinants of construction sector performance has become an important area of empirical inquiry.

Existing research in construction economics suggests that infrastructure investment stimulates output not only through direct demand effects but also through productivity spillovers and multiplier mechanisms. Studies grounded in macroeconomic growth theory argue that public infrastructure enhances production capacity and reduces transaction costs, thereby influencing sectoral GDP dynamics over time. However, empirical investigations often rely on static regression frameworks that may fail to capture the dynamic adjustment processes inherent in construction activity. Since construction output responds gradually to investment cycles, policy shifts, and price fluctuations, time-series econometric approaches provide a more appropriate analytical framework for examining these relationships (Gujarati & Porter, 2009; Wooldridge, 2016).

A key methodological challenge in analysing macroeconomic time series is the presence of non-stationarity. Economic variables such as GDP, infrastructure indices, and price levels frequently exhibit stochastic trends, which can lead to spurious regression results if not properly addressed. The Augmented Dickey–Fuller (ADF) test introduced by Dickey and Fuller (1979) has become a widely accepted tool for identifying unit roots and evaluating the statistical properties of time-series data. When non-stationary variables share a long-run equilibrium relationship, cointegration techniques provide a framework for modelling their joint dynamics. The Johansen cointegration methodology (Johansen, 1988) enables the identification of stable long-run relationships among multiple economic variables, offering a rigorous basis for empirical modelling in applied macroeconomic research.

Building on these theoretical foundations, the Autoregressive Distributed Lag (ARDL) approach has gained significant prominence in applied economics due to its flexibility in handling variables integrated of different orders and its suitability for relatively small samples. The ARDL bounds testing framework developed by Pesaran, Shin, and Smith (2001) allows researchers to simultaneously estimate short-run dynamics and long-run equilibrium relationships, making it particularly relevant for sectoral studies where data availability may be limited. Recent applications in construction economics have increasingly adopted ARDL-based approaches to evaluate the dynamic effects of infrastructure investment, inflation, and macroeconomic shocks on sectoral performance.

Within the Indian context, infrastructure expansion is frequently viewed as a structural driver of construction sector growth, while inflationary pressures represent a potential constraint through rising input costs and financial uncertainty. The interplay between these factors remains an open empirical question, particularly in emerging economies where infrastructure policy plays a central role in shaping growth trajectories. By integrating dynamic econometric techniques with sector-specific indicators, this study seeks to provide new evidence on how infrastructure activity and consumer price movements influence construction sector GDP over time.

Accordingly, this paper examines the long-run and short-run relationships between infrastructure activity, inflation, and construction sector output in India using quarterly data from 2015 to 2025. The analysis employs a log-linear econometric framework incorporating ADF unit root testing (Dickey & Fuller, 1979), Johansen cointegration analysis (Johansen, 1988), and an ARDL modelling strategy (Pesaran et al., 2001). By combining rigorous diagnostic testing with dynamic specification, the study contributes to the growing literature on infrastructure-led growth in emerging Asia–Pacific economies and provides empirical insights relevant to policymakers and construction industry stakeholders.

Despite the growing importance of infrastructure-led development in emerging economies, existing empirical studies on construction sector performance in India remain limited in three important respects. First, much of the prior literature relies on static regression approaches that do not adequately capture dynamic adjustment processes or long-run equilibrium relationships among macroeconomic variables. Second, relatively few studies integrate infrastructure activity indices with construction sector GDP within a unified time-series framework, leaving a gap in understanding how infrastructure expansion translates into sectoral economic outcomes. Third, the role of inflation as a potential constraint on construction growth has received limited empirical attention within dynamic econometric settings. Addressing these gaps, the present study makes three key contributions. It applies a rigorous econometric framework combining unit root testing, cointegration analysis, and ARDL modelling to examine both short-run and long-run relationships; it provides new empirical evidence on the structural role of infrastructure activity in shaping construction sector output in India; and it offers a diagnostically robust modelling strategy that strengthens the methodological foundation for future research in Asia–Pacific construction economics.

The remainder of this paper is structured as follows. The next section presents the theoretical background and econometric methodology, including the unit root, cointegration, and ARDL modelling framework. This is followed by a description of the data and variable construction. The subsequent section discusses the empirical results, including regression estimates, diagnostic testing, and robustness analysis. The final section concludes with key findings, policy implications, limitations, and directions for future research.

2. Theoretical Background and Econometric Framework

2.1 Economic Rationale for Infrastructure-Led Construction Growth

Infrastructure investment is widely recognised as a key driver of construction sector expansion, particularly in emerging economies. Theoretical and empirical literature suggests that public capital formation enhances productive capacity by reducing transaction costs, improving connectivity, and increasing the marginal productivity of private capital (Aschauer, 1989; Barro, 1990). In countries such as India, large-scale public spending on transportation networks, power generation, logistics systems, and urban infrastructure stimulates demand for construction services and strengthens intersectoral linkages within the broader economy.

From a macroeconomic perspective, infrastructure development generates multiplier effects through both demand-side and supply-side channels. In the short run, public investment raises aggregate demand and directly increases construction output. In the long run, infrastructure enhances total factor productivity by facilitating market integration, reducing production bottlenecks, and crowding in private investment (Calderón & Servén, 2004; Straub, 2011). These structural relationships imply that sustained growth in infrastructure activity should translate into measurable and persistent increases in construction sector output.

Within the Asia–Pacific context, infrastructure-led development strategies have played a central role in sustaining high growth trajectories. Rapid urbanisation, industrialisation, and demographic expansion have necessitated continuous expansion of transport corridors, energy systems, and housing infrastructure (World Bank, 2019). Construction firms respond to rising infrastructure investment by expanding production capacity, increasing labour utilisation, and adopting new technologies to meet growing demand. Consequently, infrastructure indices can serve as proxies for sectoral demand conditions, while construction GDP reflects realised output performance.

Inflationary pressures, represented by consumer price indices, may influence construction activity indirectly by affecting input costs, financing conditions, and investment expectations. Rising inflation can increase material and labour costs, reduce real purchasing power, and alter interest rate dynamics, thereby shaping construction sector performance (Fischer, 1993). The interaction between infrastructure investment and inflation is therefore critical in determining both short-run adjustments and long-run growth patterns in the construction industry.

Overall, economic theory and empirical evidence support the hypothesis that infrastructure expansion functions as a structural catalyst for construction sector growth, particularly in emerging economies undergoing rapid structural transformation.

2.2 Production and Efficiency Logic Behind the Model

The empirical framework of this study is grounded in neoclassical production theory, where sectoral output is determined by factor inputs, capital accumulation, and the broader macroeconomic environment (Solow, 1956; Barro, 1990). In the context of the construction sector, output is influenced not only by internal capital formation and labour utilisation but also by infrastructure development, which functions as a complementary form of public capital enhancing private sector productivity (Aschauer, 1989).

Formally, the construction production relationship can be expressed as:

$$Y_t = f(I_t, P_t)$$

where Y_t denotes construction sector output, I_t represents infrastructure activity (proxying public capital formation and sectoral demand conditions), and P_t captures price dynamics reflecting macroeconomic cost pressures.

To facilitate econometric estimation and elasticity interpretation, the model is transformed into log-linear form:

$$\ln Y_t = \alpha + \beta_1 \ln I_t + \beta_2 \ln P_t + \varepsilon_t$$

The logarithmic transformation serves multiple purposes. First, it allows estimated coefficients to be interpreted as elasticities, thereby quantifying the percentage response of construction output to changes in infrastructure activity and inflation. Second, it reduces potential heteroskedasticity and stabilises variance in macroeconomic time-series data, which often exhibit exponential growth patterns (Gujarati & Porter, 2009; Wooldridge, 2016).

From an efficiency perspective, infrastructure expansion improves the productive environment in which construction firms operate. Public infrastructure—such as transportation networks, power systems, and logistics facilities—reduces transaction costs, lowers input delivery delays, and enhances coordination efficiency across industries (Calderón & Servén, 2004). This aligns with the theoretical argument that public capital raises the marginal productivity of private capital, thereby contributing to long-run growth (Aschauer, 1989; Barro, 1990).

Accordingly, the specified model captures two complementary mechanisms. The first is a **demand-side channel**, where infrastructure investment directly stimulates construction activity through public spending. The second is an **efficiency-driven channel**, where improved infrastructure enhances productivity and resource allocation within the construction sector. This dual-channel framework is consistent with standard applied econometric production models commonly discussed in modern econometrics literature (Gujarati & Porter, 2009; Wooldridge, 2016).

2.3 Rationale for ARDL, Cointegration and Time-Series Methods

Macroeconomic time-series variables such as GDP, infrastructure indices, and price levels often exhibit stochastic trends and non-stationary behaviour. Estimating relationships among non-stationary variables using ordinary least squares (OLS) regression may produce spurious results, leading to misleading statistical inference and inflated goodness-of-fit measures (Granger & Newbold, 1974). Therefore, testing for stationarity is a necessary preliminary step in time-series analysis. To address this issue, the Augmented Dickey–Fuller (ADF) unit root framework developed by Dickey and Fuller (1979, 1981) is employed to examine the integration properties of each series and determine whether they are stationary in levels or require differencing.

When variables are integrated of order one but share a stable long-run equilibrium relationship, cointegration techniques provide an appropriate modelling strategy. The concept of cointegration, formally introduced by Engle and Granger (1987), establishes that a linear combination of non-stationary variables may itself be stationary, indicating the presence of a meaningful long-run relationship. For multivariate systems, the Johansen (1988, 1991) maximum likelihood methodology enables identification and estimation of multiple cointegrating vectors within a Vector Autoregressive (VAR) framework. This approach is particularly useful when examining interdependent macroeconomic variables such as construction output, infrastructure activity, and price levels.

Building on these foundations, the Autoregressive Distributed Lag (ARDL) modelling framework developed by Pesaran and Shin (1999) and extended by Pesaran, Shin, and Smith (2001) provides a flexible approach for estimating both short-run dynamics and long-run equilibrium effects within a single reduced-form equation. A key advantage of the ARDL bounds testing approach is that it can be applied irrespective of whether variables are purely I(0), purely I(1), or mutually cointegrated, provided none is integrated of order two. Moreover, ARDL models perform well in small samples and allow for different optimal lag structures across variables (Narayan, 2005). This flexibility makes the ARDL framework particularly suitable for quarterly construction sector data, where adjustment dynamics may differ across infrastructure and price variables.

Overall, the combined use of unit root testing, cointegration analysis, and ARDL estimation ensures econometric robustness, avoids spurious regression bias, and captures both equilibrium relationships and short-run adjustment processes in infrastructure-led construction growth models.

2.4 Model Specification and Equations

Following the log-linear production framework, the baseline static model is specified as:

$$\ln GDP_t = \alpha + \beta_1 \ln ICI_t + \beta_2 \ln CPI_t + \varepsilon_t$$

where:

- $\ln GDP_t$= logarithm of construction sector GDP
- $\ln ICI_t$= logarithm of infrastructure activity index
- $\ln CPI_t$= logarithm of consumer price index

To capture dynamic adjustments, an ARDL (p, q, r)structure is implemented:

$$\ln GDP_t = \alpha + \sum_{i=1}^{p} \phi_i \ln GDP_{t-i} + \sum_{j=0}^{q} \theta_j \ln ICI_{t-j} + \sum_{k=0}^{r} \gamma_k \ln CPI_{t-k} + u_t$$

This formulation allows current construction output to depend on its own past values as well as contemporaneous and lagged infrastructure and price effects. The inclusion of lagged terms reflects gradual adjustment processes within the construction industry, where project execution, investment cycles, and policy impacts unfold over time.

Diagnostic procedures, including multicollinearity assessment, autocorrelation testing, and heteroskedasticity checks, are subsequently employed to validate the econometric specification and ensure the robustness of empirical results.

3. Data Description and Variable Construction

3.1 Data Sources and Coverage

This study employs quarterly time-series data to examine the relationship between infrastructure activity, inflation dynamics, and construction sector output in India. The dependent variable is construction sector gross domestic product (GDP), obtained from official macroeconomic statistics published by the Ministry of Statistics and Programme Implementation (MOSPI). The construction sector GDP series is measured at constant prices to capture real output dynamics and avoid inflation-induced distortions. Quarterly observations span the period from Q4 2015 to Q3 2025, providing a balanced sample suitable for dynamic time-series modelling and ARDL estimation.

Infrastructure activity is proxied using the Overall Index of the Eight Core Industries (ICI), compiled by the Office of the Economic Adviser under the Ministry of Commerce and Industry. The ICI reflects performance across key infrastructure-related sectors including electricity, coal, steel, cement, crude oil, refinery products, natural gas, and fertilisers. Together, these industries account for a substantial share of the Index of Industrial Production (IIP), making the ICI a widely recognised indicator of infrastructure momentum and industrial capacity in India. Monthly index values were converted into quarterly averages to ensure temporal consistency with construction GDP and to reduce high-frequency volatility.

Inflation dynamics are captured using the Consumer Price Index (CPI) for India, obtained from official CPI publications of the Ministry of Statistics and Programme Implementation. The CPI measures changes in the general price level of a representative consumption basket and serves as a standard indicator of inflationary pressures in the economy. Monthly CPI values were aggregated into quarterly averages to align with the frequency of the dependent variable. The CPI is included as a proxy for macroeconomic price pressures that may influence construction activity through input costs, financing conditions, and real investment decisions (Fischer, 1993).

All variables are transformed into natural logarithms prior to estimation to allow elasticity interpretation and mitigate heteroskedasticity commonly observed in macroeconomic time-series data (Gujarati & Porter, 2009; Wooldridge, 2016).

3.2 Variable Definition and Transformation

Three primary variables are used in the empirical analysis:

- **Construction GDP (GDP)**: Measured in INR billions, representing the economic output of the construction sector.
- **Infrastructure Index (ICI)**: Overall index of the eight core industries, used as a proxy for infrastructure activity and sectoral demand conditions.
- **Consumer Price Index (CPI)**: Indicator of inflation and general price movements within the economy.

To stabilise variance and interpret coefficients as elasticities, all variables are transformed into natural logarithmic form:

$$\ln GDP_t, \ln ICI_t, \ln CPI_t$$

Log transformation also helps mitigate scale differences across variables and reduces potential heteroskedasticity, which is common in macroeconomic time-series data.

3.3 Data Alignment and Pre-Processing

Because the original datasets were available at different frequencies, several preprocessing steps were implemented prior to estimation. Monthly ICI and CPI series were converted into quarterly averages to match the quarterly GDP observations. The data were organised in calendar-year quarters, consistent with the reporting format of the GDP series. Observations were checked for missing values and structural inconsistencies before transformation into logarithmic form.

The final dataset consists of 40 quarterly observations, providing sufficient degrees of freedom for estimating a log-linear ARDL specification. Lagged variables were generated within the econometric framework to capture dynamic adjustment processes, reflecting the gradual response of construction output to infrastructure expansion and price changes.

3.4 Econometric Preparation and Sample Characteristics

Prior to estimation, all variables were examined for consistency in frequency, scale, and temporal alignment. Monthly infrastructure and price indices were aggregated into quarterly averages to ensure compatibility with the quarterly construction GDP series. The final dataset contains 40 quarterly observations, which is considered adequate for autoregressive distributed lag (ARDL) modelling, as the ARDL framework is specifically designed to perform reliably under relatively small sample conditions (Pesaran, Shin, & Smith, 2001).

Natural logarithmic transformation was applied to each variable to reduce potential heteroskedasticity, stabilise variance, and allow estimated coefficients to be interpreted as elasticities. Log transformation is commonly employed in macroeconomic time-series modelling because it linearises exponential growth patterns and improves the statistical properties of regression residuals (Gujarati & Porter, 2009; Wooldridge, 2016).

Given the visible trending behaviour in construction GDP, infrastructure activity, and consumer prices, the study adopts a structured time-series approach. Unit root testing is conducted to assess stationarity, followed by cointegration analysis to evaluate long-run equilibrium relationships among the variables. The use of lagged variables within the ARDL framework reflects the gradual adjustment processes typical of construction sector dynamics, where investment decisions, infrastructure expansion, and price effects influence output with temporal delays.

Overall, these preprocessing and econometric preparation steps ensure that the dataset satisfies the assumptions required for dynamic modelling while maintaining consistency with established practices in applied macroeconomic analysis.

4. Methodology

This study adopts a structured time-series econometric framework to examine the dynamic relationship between infrastructure activity, inflation, and construction sector output in India. The methodological approach consists of four main stages: unit root testing, cointegration analysis, ARDL model estimation, and post-estimation diagnostic testing. The sequence ensures that statistical inference is valid and that both long-run equilibrium relationships and short-run adjustments are appropriately captured.

4.1 Unit Root Testing

Macroeconomic time-series variables such as GDP, infrastructure indices, and consumer price indices typically exhibit stochastic trends. Estimating relationships among non-stationary variables using ordinary least squares (OLS) may generate spurious regression results, leading to misleading statistical inference (Granger & Newbold, 1974). Therefore, it is essential to examine the order of integration of each variable before proceeding with long-run estimation.

To test for stationarity, this study employs the **Augmented Dickey–Fuller (ADF) test**, developed by Dickey and Fuller (1979, 1981). The ADF test extends the basic Dickey–Fuller framework by including lagged differences of the dependent variable to correct for serial correlation in the residuals.

The ADF regression can be expressed as:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{k} \gamma_i \, \Delta Y_{t-i} + \varepsilon_t$$

where:

- Δ denotes the first-difference operator
- k represents the number of lagged differences
- ε_t is the white-noise error term

The null hypothesis (H_0: β = 0) indicates the presence of a unit root (non-stationarity), while the alternative hypothesis suggests stationarity. If variables are found to be integrated of order one, I(1), cointegration analysis becomes appropriate to examine long-run equilibrium relationships (Enders, 2015).

4.2 Johansen Cointegration Analysis

When multiple macroeconomic variables are individually non-stationary but move together over time, they may share a stable long-run equilibrium relationship. This phenomenon is known as cointegration (Engle & Granger, 1987).

To examine whether construction GDP, infrastructure activity, and consumer prices are cointegrated, this study applies the **Johansen (1988, 1991) maximum likelihood cointegration procedure**. Unlike the Engle–Granger two-step approach, the Johansen method allows for testing multiple cointegrating vectors within a multivariate vector autoregressive (VAR) framework.

The Johansen methodology evaluates the rank of the long-run coefficient matrix using the trace statistic and the maximum eigenvalue statistic. The trace test examines the null hypothesis that the number of cointegrating relationships is less than or equal to r against a general alternative.

Evidence of at least one cointegrating vector implies the existence of a stable long-run equilibrium among infrastructure activity, inflation, and construction output. In such a case, dynamic models incorporating both long-run and short-run adjustments are econometrically justified (Johansen, 1995).

4.3 Autoregressive Distributed Lag (ARDL) Specification

Following the assessment of stationarity and cointegration properties, this study estimates an **Autoregressive Distributed Lag (ARDL)** model to capture the dynamic interactions among construction output, infrastructure activity, and inflation.

The ARDL framework developed by Pesaran and Shin (1999) and further formalised in Pesaran, Shin, and Smith (2001) is particularly appropriate when variables are integrated of order I(0), I(1), or a mixture of both, but not I(2). An important advantage of the ARDL approach is its suitability for small sample sizes and its ability to estimate both short-run dynamics and long-run relationships within a single reduced-form equation (Pesaran et al., 2001).

The general ARDL (p, q, r)model used in this study is specified as:

$$\ln GDP_t = \alpha + \sum_{i=1}^{p} \phi_i \ln GDP_{t-i} + \sum_{j=0}^{q} \theta_j \ln ICI_{t-j} + \sum_{k=0}^{r} \gamma_k \ln CPI_{t-k} + u_t$$

where:

- $\ln GDP_t$represents the logarithm of construction sector output,

- $\ln ICI_t$ denotes infrastructure activity,
- $\ln CPI_t$ captures inflation dynamics, and
- u_t is the error term.

The inclusion of lagged dependent and independent variables reflects gradual adjustment processes in the construction sector. Infrastructure investment typically affects output over multiple periods due to planning lags, capital accumulation, and implementation delays. Similarly, inflationary pressures influence construction costs and investment decisions over time.

When cointegration is present, the ARDL model can be re-parameterised into an **Error Correction Model (ECM)** form, allowing estimation of the speed at which short-run deviations adjust toward long-run equilibrium (Pesaran et al., 2001; Narayan, 2005).

4.4 Diagnostic Tests and Model Validation

To ensure econometric reliability, several post-estimation diagnostic procedures are conducted.

Multicollinearity among explanatory variables is evaluated using the **Variance Inflation Factor (VIF)**, which measures the degree to which the variance of an estimated coefficient increases due to collinearity (Gujarati & Porter, 2009). Excessively high VIF values may distort statistical inference.

Serial correlation in residuals is assessed using the **Durbin–Watson statistic**, which detects first-order autocorrelation in regression disturbances (Durbin & Watson, 1950, 1951). Absence of serial correlation ensures unbiased and efficient estimation under classical assumptions.

Heteroskedasticity is examined using the **Breusch–Pagan test**, which evaluates whether the variance of residuals is constant across observations (Breusch & Pagan, 1979). Addressing heteroskedasticity is essential to maintain valid standard errors and hypothesis testing.

Together, these diagnostic procedures confirm whether the estimated ARDL model satisfies the classical regression assumptions and whether inference regarding infrastructure-led construction growth is statistically reliable.

4.5 Estimation Strategy

The empirical analysis follows a structured and sequential estimation strategy consistent with established practices in applied time-series econometrics (Enders, 2015; Gujarati & Porter, 2009).

First, a **log-linear static regression model** is estimated to provide a preliminary benchmark relationship between construction GDP, infrastructure activity, and consumer prices. This specification offers an interpretable baseline and enables initial evaluation of coefficient signs, economic plausibility, and multicollinearity concerns.

Second, recognising the potential non-stationarity of macroeconomic time series, unit root and cointegration tests are performed. If variables exhibit integration properties beyond I(0), dynamic modelling becomes necessary to avoid spurious regression results (Granger & Newbold, 1974).

Third, the ARDL framework is implemented to estimate both short-run and long-run dynamics simultaneously. The inclusion of lagged terms reflects gradual sectoral adjustment to infrastructure expansion and price changes.

Finally, diagnostic and robustness tests are conducted to validate the econometric specification. This structured estimation sequence enhances transparency, strengthens inferential validity, and ensures consistency with established empirical standards in infrastructure-growth research.

The following section presents the empirical findings derived from the estimated models, including unit root and cointegration results, ARDL estimation outcomes, and diagnostic tests. The results are interpreted within the context of infrastructure-led construction growth and macroeconomic dynamics in India.

5. Empirical Results

5.1 Baseline Regression Results

The baseline log–linear regression provides an initial assessment of the relationship between construction sector output and key macroeconomic drivers in India. The model demonstrates strong explanatory power, with an $R^2$of approximately 0.943, indicating that infrastructure activity and price dynamics jointly account for a substantial proportion of variation in construction GDP. The coefficient of $\ln ICI(\approx 1.998)$ is positive and highly statistically significant, highlighting the dominant role of infrastructure expansion in driving sectoral output. This finding is consistent with infrastructure-led growth theories which emphasise the productivity-enhancing effects of public capital and large-scale development projects (Aschauer, 1989; Calderón & Servén, 2010).

In contrast, the coefficient of $\ln CPI(\approx -0.167)$ is negative but statistically insignificant, suggesting that inflationary pressures may exert only a modest and uncertain influence on construction performance. Similar outcomes have been documented in macro-sectoral studies where price movements affect costs but do not necessarily determine real output dynamics (Gujarati & Porter, 2009).

While these static estimates provide preliminary insights, the trending nature of macroeconomic variables raises the possibility of spurious regression, a well-known issue in non-stationary time-series analysis (Granger & Newbold, 1974). Consequently, formal time-series diagnostics were conducted to validate the long-run relationships among the variables.

5.2 Stationarity and Cointegration Findings

Augmented Dickey–Fuller (ADF) tests indicate that $\ln GDP$, $\ln ICI$, and $\ln CPI$are non-stationary in levels, with p-values exceeding conventional significance thresholds. Such outcomes are consistent with macroeconomic indicators characterised by persistent growth trajectories (Dickey & Fuller, 1979). The presence of unit roots necessitates the application of cointegration techniques to examine whether a stable long-run equilibrium exists among the variables (Engle & Granger, 1987).

The Johansen cointegration test confirms one cointegrating relationship. The trace statistic rejects the null hypothesis of no cointegration at the 5% level, implying a stable equilibrium structure linking infrastructure activity, price dynamics, and construction GDP over time. This result aligns with multivariate cointegration theory, which emphasises the joint evolution of macroeconomic variables within long-run equilibrium systems (Johansen, 1988; Johansen, 1991).

5.3 Dynamic ARDL Model Results

To capture both short-run adjustments and long-run dynamics, an ARDL(1,1,1) specification was estimated. The lagged dependent variable $\ln GDP_{t-1}$(0.345, p = 0.014) is positive and statistically significant, indicating persistence in construction output and gradual adjustment to macroeconomic shocks. Such dynamic behaviour reflects adjustment costs and sectoral rigidities commonly observed in investment-intensive industries (Pesaran, Shin, & Smith, 2001).

Infrastructure activity remains the most influential determinant of construction sector performance. The contemporaneous $\ln ICI$coefficient (2.135, $p < 0.001$) indicates a strong positive elasticity, supporting the view that infrastructure investment acts as a catalyst for construction growth by stimulating demand for materials, labour, and capital services (Calderón & Servén, 2010). However, the negative and significant lagged $\ln ICI$term (−1.207, $p < 0.001$) suggests partial correction effects following rapid expansions, possibly reflecting project completion cycles and resource reallocation across sectors.

The role of consumer prices appears weaker and less consistent. The contemporaneous $\ln CPI$coefficient is negative but statistically insignificant, while the lagged term shows only marginal significance. These findings suggest that inflation influences construction activity indirectly through financing conditions and cost adjustments rather than acting as a primary driver of output fluctuations.

5.4 Diagnostic Tests and Model Robustness

A series of diagnostic tests were conducted to evaluate model adequacy. The Durbin–Watson statistic of approximately 2.15 indicates no serious autocorrelation, suggesting that the ARDL lag structure adequately captures serial dependence in the data. The Breusch–Pagan heteroskedasticity test yields a p-value of 0.141, implying stable residual variance and reliable standard errors.

Variance Inflation Factor (VIF) values are relatively high, reflecting strong co-movement among trending macroeconomic variables. Such outcomes are typical in cointegrated systems and do not necessarily signal harmful multicollinearity (Gujarati & Porter, 2009). The stability of coefficient signs across specifications and the confirmed cointegration relationship reinforce the robustness of the empirical results.

6. Discussion and Economic Interpretation

The empirical findings reveal a clear hierarchy of influences shaping construction sector dynamics in India. Infrastructure activity emerges as the dominant transmission channel, exerting strong and immediate effects on construction GDP. This result supports endogenous growth perspectives that emphasise infrastructure as a productivity-enhancing input capable of generating multiplier effects across sectors (Aschauer, 1989; Calderón & Servén, 2010).

The significant lagged dependent variable indicates that adjustment processes within the construction sector are gradual rather than instantaneous. Such persistence reflects planning horizons, contractual rigidities, and capital-intensive investment structures that slow the response of output to macroeconomic shocks. The negative lagged infrastructure effect further suggests cyclical adjustment patterns following rapid expansion phases, consistent with dynamic investment behaviour observed in infrastructure-driven economies.

Inflationary dynamics appear to play a secondary role. Although price pressures may influence costs and financing conditions, their direct impact on output growth remains limited relative to infrastructure-driven demand. This finding aligns with empirical evidence showing that structural investment policies often exert stronger long-term effects on sectoral output than short-term price fluctuations.

The consistency between static regression estimates and the dynamic ARDL framework strengthens confidence in the central conclusion: construction sector growth is primarily infrastructure-led rather than inflation-driven. The presence of a stable cointegrating relationship further suggests that these dynamics reflect a long-run equilibrium embedded within the broader macroeconomic environment rather than temporary correlations (Engle & Granger, 1987; Pesaran et al., 2001).

From a policy perspective, the results highlight the importance of sustained infrastructure investment as a catalyst for sectoral expansion and broader economic development. At the same time, the observed lag structures indicate that policymakers should anticipate delayed responses to investment initiatives, reinforcing the need for long-term planning horizons and coordinated fiscal strategies.

7. Limitations, Conclusions and Future Research Directions

This study develops an econometric framework to examine the relationship between infrastructure activity, inflation dynamics, and construction sector output in India using log-transformed time-series modelling and an ARDL specification. Unit root tests indicate that the variables are non-stationary in levels, while the Johansen cointegration results confirm the presence of a long-run equilibrium relationship among construction GDP, infrastructure expansion, and consumer prices. The empirical findings consistently highlight infrastructure activity as the dominant explanatory factor. The positive and statistically significant coefficient associated with infrastructure development suggests that sustained infrastructure investment acts as a structural driver of construction sector growth. In contrast, inflation exhibits a negative but statistically weak influence, implying that short-term price pressures do not significantly constrain construction output once long-run dynamics are incorporated. Diagnostic tests, including Durbin–Watson and Breusch–Pagan statistics, indicate no serious issues of serial correlation or heteroskedasticity, supporting the econometric reliability of the model.

Despite these contributions, several limitations should be acknowledged. The analysis relies on a relatively small quarterly sample, which may limit statistical power and reduce the ability to capture structural breaks or policy shocks. The presence of strong multicollinearity among macroeconomic indicators reflects the interconnected nature of infrastructure and price dynamics in emerging economies, but it may also inflate variance estimates and complicate coefficient interpretation. Furthermore, the study focuses on aggregate macroeconomic indices and does not incorporate firm-level construction data, regional disparities, or project-specific efficiency measures. The modelling framework is primarily linear and may not fully capture nonlinear adjustment processes or optimisation behaviour within the construction industry.

Future research can build upon this framework by integrating additional macroeconomic and financial variables such as interest rates, public capital expenditure, or credit availability to better capture investment cycles. Incorporating optimisation-based approaches or nonlinear econometric techniques may provide deeper insights into resource allocation efficiency within the construction sector. Expanding the analysis to a multi-country Asia–Pacific panel would enhance comparative understanding and improve external validity. Moreover, combining traditional econometric models with machine learning methods could improve forecasting accuracy and reveal complex interactions among infrastructure investment, economic policy, and construction sector performance.

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