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IMPACT OF PHYSICAL AND SOCIAL INFRASTRUCTURES ON INCLUSIVE GROWTH IN INDIA

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Abstract: The role of infrastructure as a key driver of inclusive growth has been well established due to its positive role in improving quality of life, particularly for the poor. The purpose of this paper is to provide an empirical evidence on the nexus between infrastructure and inclusive growth in India. For the said purpose, a physical infrastructure index (PHYINF), a social infrastructure index (SOCINF), and an inclusive growth index (IGI) are constructed to analyze the impact of different sub-sectors of infrastructure on inclusive growth for the period 1991 to 2015. Bivariate and multivariate cointegration tests are used to analyze the long-run association between PHYINF, SOCINF, and IGI. In addition, Granger causality test is performed to assess the direction of causality between the variables. Results indicate that, in the long-run, physical infrastructure and social infrastructure foster inclusive growth as both the infrastructures have significant positive effect on inclusive growth. A short-run association is also found between IGI, PHYINF, and SOCINF where PHYINF and SOCINF positively affect IGI. The results of causality tests confirm the existence of unidirectional causality from both physical and social infrastructure to inclusive growth. From the policy suggestion, the study concludes that policies facilitating infrastructural services are crucial for achieving inclusive growth.

Index Terms - Inclusive growth, Infrastructure, Physical infrastructure, Social infrastructure, Cointegration Granger causality.

I. INTRODUCTION

Infrastructure as a key driver of inclusive growth[1] has been well identified due to its positive role in improving quality of life, particularly for the poor. Well-developed infrastructure creates additional jobs for the economy, expanding production capacities and reduce the cost of production through the improvement of transportation connectivity, increasing access to economic opportunities and can increase social inclusion. In addition, better infrastructure promotes high, efficient, and sustained growth that lower income inequality and facilitates a meaningful and sustainable poverty reduction (Calderon and Serven, 2005; World Bank, 2009) Empirical evidences also show that infrastructure investment can have potential impact in promoting inclusive growth and poverty reduction (Ali and Pernia, 2003; Raihan, 2011). The importance of inclusive growth has gained

[1] By inclusive growth we mean economic growth that ensure equal opportunity to all, particularly to the poor and, broad based across sectors so that everyone can participate in the growth process.

momentum among the policymakers and researchers in the early 2000s due to its considerable role in reducing inequality. Since then, a number of research work have been conducted. Most of them were based on the definition of inclusive growth (Ali and Son, 2007; Habito, 2009; Ianchovichina and Lundstrom, 2009; Klasen, 2010, etc.), methodologies for its measurements (Ali & Son, 2007; Mckinley, 2010; Anand et al., 2013; Udah and Ebi, 2013; Vellala et al., 2016; Munir and Ullah, 2018, Mitra and Das, 2018; Aggarwal, 2021, etc.) and micro and macro factors (Aoyagi and Ganelli, 2015; Khan et al., 2016; Oluseye and Gabriel, 2017, etc.) that promote inclusiveness in a region. Various attempts have been made to quantify the role of infrastructure in promoting inclusiveness but none of the study clearly provides strong empirical evidences on this nexus particularly, when it comes to the role of different infrastructural sub-sectors in promoting inclusive growth. In most cases, they have come to a similar conclusion that 'availability of infrastructure services particularly transport, health and education facilitates production and expand economic opportunities that spur growth, which in turn helps raise incomes and reduce poverty and hence, promote inclusiveness. Empirical evidences also showed that investment on infrastructural projects can have potential impact in promoting inclusiveness and poverty reduction (Ali and Pernia, 2003; Raihan, 2011). In this context, the present study makes an attempt to provide empirical evidences to understand the nexus between infrastructure and inclusive growth. Understanding such nexus would be vital for the policymakers to formulate appropriate infrastructure policies for promoting greater inclusiveness. This study uses physical forms of infrastructure namely, transport, power, and telecommunication and social forms of infrastructure namely, health and education. These infrastructure services are synonymous to development, and the lack of such services signal barriers to growth and overall development. So, use of these services as a measure of infrastructure is well justified. The study also considers the multidimensionality nature of inclusive growth and measures it accordingly. The study considers five major dimensions of inclusive growth namely, economic inclusion, environmental sustainability, gender empowerment, human capability, and financial inclusion. Suitable indicators under each dimension are taken to measure inclusive growth. The list of the indicators and the dimensions of inclusive growth are reported in the data and methodology section. A wide range of econometric techniques with the aid of stationarity, cointegration, and Granger causality tests are used to quantify the nexus between inclusive growth and infrastructure namely, physical and social infrastructure in the context of India over the period 1991 to 2015. The time period of the study has significant economic, social and political importance as Indian economy shifted its focus towards building a sustainability and inclusiveness economy in the early 1990s. This study makes an attempt to access the impact of different sub-sectors of infrastructure in inclusive growth and therefore, make a notable contribution in the emerging inclusive growth literature. The structure of this paper is as follows; section 2 summarizes the existing literature. Section 3 describes the data and Section 4 explains the research methodology. Section 5 presents and discusses the empirical findings. Finally, the study concludes in the section 6.

II. REVIEW OF LITERATURE

Infrastructure development can promote inclusive growth as it raises income of the people, facilitates poverty reduction, creates new employment opportunities, reduces production cost through improvements of connectivity, expands overall production capacity and improves access to key facilities – this view is well recognized by the policy makers and urban planners. Empirical studies analyzing the relationship between infrastructure and inclusive growth have also supported it. However, such studies are limited and most of them analyzed the role infrastructure in either poverty reduction or in declining inequality (Ali and Pernia, 2003; Fan, Zhang and Zhang, 2004; Escobal and Ponce, 2008; Chotia and Rao 2015; Parikh et al., 2015 etc.) and then justified this interlinkage. In this line, Bhattacharya et al., (2020) evaluated the role of infrastructure development in income growth and poverty reduction by focusing on electricity, roads, health and education sectors in 18 major Indian states. They found that development of road, electricity, and education infrastructure has a positive and significant impact on economic growth while the impact of health infrastructure is insignificant. On the 21 other hand, their analysis suggested that health and electricity infrastructure have a strong impact on poverty reduction. They concluded that infrastructure augments economic growth and helps in poverty reduction and thereby makes growth inclusive. Nagraha et al., (2020) have examined a similar relationship between infrastructure development, economic growth and income inequality in the context of Indonesia during 2010-2016. Their findings revealed that, basic infrastructure, namely, clean water, electricity distribution, and road lengths are positively associated with economic growth and indirectly reduces inequality. They concluded that government should encourage investment in basic infrastructure and transportation to improve economic performance sustainably. Batool et al., (2020) found a positive association between education, health, transportation and telecom and inclusive growth in Pakistan and concluded that investment in human and physical infrastructure are essential to foster economic advancement. Mutiiria et al., (2020) assessed the relationship between infrastructure and inclusive growth in sub-Saharan Africa (SSA). They have used panel data of 31 SSA over the period 2003-2017 and found a positive link between infrastructure and inclusive growth. Their results showed that energy, transpose, and ICT are important components of infrastructure that play an important role in the distribution of income. Their concluded that appropriate policies for increasing access and affordability of infrastructure services can promote inclusion.

III. DATA AND SOURCE OF DATA

The present study uses annual time-series data for the estimating the impact of physical and social infrastructure on inclusive growth. The time period of the study remains between 1991 to 2015. The time period of the study is chosen by regards to the availability of data. The indicators of the variables (i.e., inclusive growth, physical infrastructure, and social infrastructure infrastructure) under study are obtained mainly from the World Bank and EPWRF – India Time Series and the CMIE data-base. The complete list of indicators and their sources are reported in Table A.1 and A.2 in the appendix. The multidimensionality of 'inclusiveness' in growth is measured through the construction of inclusive growth index (IGI) where 8 different developmental variables (categorized into economic expansion, environmental sustainability, gender equity, human development, and financial inclusion) are used as its components. On the other hand, Transport, telecommunication, and Power infrastructure indicators are used to construct physical infrastructure index

(PHYINF) whereas education and health infrastructure indicators are taken to construct social infrastructure index (SOCINF).

3.1. Index Construction: Normalization and Weights of Indicators

Inclusive growth and infrastructure are multidimensional concepts. Several individual indicators in development economics provide useful information on various aspects of inclusiveness and infrastructure. Such indicators can be used to measure these concepts. However, these individual indicators may provide incomplete information and approaches involving use of such indicators reflecting multidimensional aspects of inclusiveness and infrastructure can be questionable and doubtful. The present study therefore employed a comprehensive measure combining information on all aspects of 'inclusiveness' in growth and infrastructure namely, physical and social infrastructure and explored their underlying economic relationship.

The first step of composite index construction is to aggregate its dimensions. This can be done in several ways. However, two popular methods of aggregating the dimensions are: combining the dimensions by taking their average either arithmetically or geometrically and by the use of principal component analysis (PCA). While the former assign equal weight to each indicator, the later computes weights through an orthogonal transformation of the linearly uncorrelated principal components. We have used equal-weighted indexed method to assign the weights of the indicators of inclusive growth, physical infrastructure and social infrastructure. The average based indexed method is a unit free measures, easy to interpret and satisfies some inherent properties of a good composite index namely, homogeneity, monotonicity, boundedness (Sarma, 2015). This method is not biased towards one or more of the indicators and comprises important information from all the indicators.

Present study uses equal-weighted index method for constructing the IGI, PHYINF, and SOCINF. All indicators are normalized before assigning weights to them and this is done by using the following formula:

$$NV_{it} = \left[\frac{Y_{it} - \min Y_{it}}{\max Y_{it} - \min Y_{it}}\right] \tag{1}$$

and

$$NV_{it} = \left[\frac{maxY_{it} - Y_{it}}{max\,Y_{it} - min\,Y_{it}}\right] \tag{2}$$

$\forall i = 1\,(1)3; t = 1(1)25$ for the *i*th indicator and *t*th time period. Here, the calculated normalized values vary from zero (when Y_{it} = min Y_{it}) to one (when Y_{it} = max Y_{it}). For some variables like, GDP per-capita, zero indicates the worst value and one indicates the highest value. However, for some indicators i.e., CO2 and IMR, we use the following formula (equation 2) to calculate their normalized values. For such variables, one indicates the worst value and zero indicates the best value. Table A.1, A.2 in the appendix present the final weights to each of the indicators in the calculation of IGI, PHYINF, and SOCINF.

3.2. Theoretical framework

To analyze the impact of physical and social infrastructure on inclusive growth in India we employ a standard empirical time-series regression model. Ceteris paribus, we assume inclusive growth function in India as follows

$$IGI = f(PHYINF, SOCINF) \tag{3}$$

Where, IGI is our dependent variable, and PHYINF & SOCINF are the independent variables. It is expected that both PHYINF and SOCINF will have some positive impact on IGI since providing access of such infrastructure to all, particularly to the poor, a country can reduce inequality and promote social mobility and hence achieve inclusiveness in growth. The econometric specification of eqn. (3) can be written as

$$IGI_t = \beta_1 + \beta_2 PHYINF_t + \beta_3 SOCINF_t + u_t \quad (4)$$

Here, the parameters β_2 and β_3 quantify the effect of each the explanatory variables on the explained variable IGI whereas, the parameter β_1 represents the aggregate IGI to change over time. Furthermore, we use specific time-series models in line with the nature of the data in the methodology section.

IV. RESEARCH METHODOLOGY

4.1. Statistical tools and econometric models

The presence of co-integration between the variables exhibits a long-run equilibrium relationship where economic forces are in balance and there is no tendency to change (Cheng, 1999). Two conventional tests namely, Engle-Granger cointegration (1987) test and Johansen Co-integration (1988) test are there to analyze the long-run association between the variables. While the first approach is used in the bivariate case, the second approach is employed in a multivariate framework to estimate the long-run relationship between the variables. In this article, we use both the approaches to explore the nexus between infrastructure and inclusive growth.

4.1.1. Engle and Granger approach to Cointegration

Engel and Granger (1987) pointed out the use of cointegration test as a pre-test to avoid spurious regression and to detect the common trend of any time series. They showed that two *I* (1) time series may be cointegrated if their linear combination is *I* (0). In such situation a long run equilibrium relationship may exists between them and Granger causality test can be applied to assess the direction of short run causality of the underlying series in at least on direction in *I* (0) variables. Engle and Granger test of cointegration method applies ADF test on the residuals estimated from the cointegrating regression (Maparu and Mazumder, 2017). The ADF test equation of such case is:

$$\Delta\hat{\varepsilon}_t = \alpha\hat{\varepsilon}_{t-1} + \sum_{i=1}^{\rho} \beta_i \Delta\hat{\varepsilon}_{t-i} + \mu_t \quad (5)$$

Now by testing the null hypothesis $H_0: \alpha = 0$, against the alternative $H_1: \alpha \neq 0$, one can conclude whether $\hat{\varepsilon}_t$ is *I* (0) indicating that two series are cointegrated or not indicating no cointegration between the underlying variables. In case the variables are cointegrated, one can use the residuals of Eq. (5) to estimate the error-correction model and analyse the long-run and short-run effects of the variables (Asteriou, and Hall, 2007).

4.1.2. Johansen approach to Cointegration

One of the major problems associated with Engle and Granger test of cointegration is that it uses single equation method and cannot applicable for more than two variables i.e., in case of multivariate model. Another limitation of this method is that in case of small sample the result of cointegration may change depending upon which variable is used as the regressor[2]. These problems can be solved by the use of Johansen (1991,

[2] See Bhaumik (2015), pp. 275

1995) test of cointegration. Johansen test of Co-integration (1988) proposes two different likelihood ratio tests namely; the Trace test and Maximum Eigen value test which are shown in equations (6) and (7).

$$\tau_{trace}(r) = -T\sum_{i=r+1}^{n} ln\,(1-\hat{\tau}_i) \tag{6}$$

$$\tau_{max}(r, r+1) = -Tln(1-\hat{\tau}_{r+1} \tag{7}$$

Here T is the sample size and $\hat{\tau}_i$ is the i^{th} largest canonical correlation. Trace test tests the null hypothesis of *r* co-integrating vectors against the alternative hypothesis of *n* co-integrating vectors while the Maximum Eigen value test tests the null hypothesis of *r* co-integrating vectors against the alternative hypothesis of *r +1* co-integrating vectors (Hjalmarsson & Österholm, 2007).

4.1.3. Vector Error Correction Model (VECM)

The co-integrating equation gives long run relationship between the variables and does not shed any light on short run dynamics. However, its existence indicates that there must be some short-term forces which are responsible for keeping the long-run relationship intact (Bhaumik, 2015). The study then applies Vector Error Correction Model (see equation 8) to assess the long-run relationship inclusive growth, physical infrastructure and social infrastructure in a multivariate framework. In a VECM, the first difference of each endogenous variable is regressed on the lagged first difference of all the endogenous variables in the system along with one period lagged-cointegrating equation.

$$\begin{bmatrix} \Delta IGI_t \\ \Delta PHYINF_t \\ \Delta SOCINF_t \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \\ \alpha_{30} \end{bmatrix} + \sum_{i=1}^{\rho} \begin{bmatrix} \alpha_{11i} & \alpha_{12i} & \alpha_{13i} \\ \alpha_{21i} & \alpha_{22i} & \alpha_{23i} \\ \alpha_{31i} & \alpha_{32i} & \alpha_{33i} \end{bmatrix} \begin{bmatrix} \Delta IGI_{t-i} \\ \Delta PHYINF_{t-i} \\ \Delta SOCINF_{t-i} \end{bmatrix} + \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix} ECT_{t-1} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \tag{8}$$

Here, $ECT_{\,t-1}$ is the lagged value of the error correction term derived from the following cointegration equation: $IGI_t = a_1 PHYINF_t + a_2 SOCINF_t$ (9)

The lagged value of the error correction term measures the magnitude of the past equilibrium and its coefficient λ_i measures the speed at which the system will return to its long-run equilibrium path if there occurs any short run disturbance. However, the coefficients of the lagged differenced independent variables capture the short run-dynamics and their significance indicate the short-run causality whereas, the lack of significance of the coefficients indicate no short-run causality among the variables. The study uses some diagnostic tests to check the stability and fitness of the model such as LM (Lagrange-Multiplier**)** test for detecting autocorrelation in the residuals of the model, JB (Jarque-Bera) test for examining whether the residuals of the mode are normally distributed or not and CUSUM of square test for the model's stability.

V. RESULTS AND DISCUSSION

5.1. Trend Analysis

In this section, the study presents the scenario of inclusive growth, physical infrastructure, and social infrastructure with the aid of prepared indices and also analyses the time trend of the indices to determine their pattern over time. Fig 1 below represents the trends in IGI, PHYINF, and SOCINF in India from 1991 to 2015. The y-axis measures the index scores of the variables and x-axis measures the years under review.

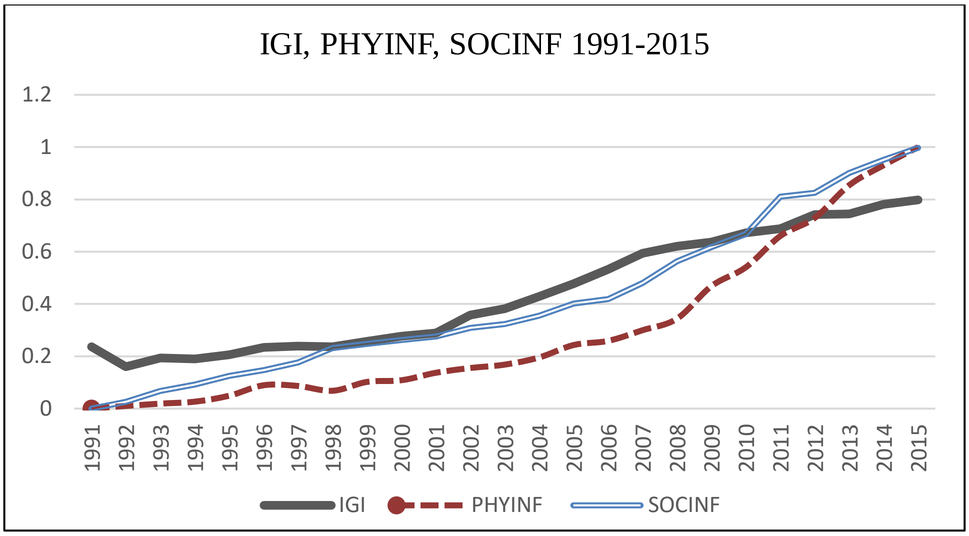

Fig 1: Trends in IGI, PHYINF, and SOCINF

Source: Author's Computation

The index score of inclusive growth has declined between 1991 to 1992 and then steadily increased thereafter. The infrastructure indices on the other hand, exhibited a steady and continuous rise during this period though, SOCINF has shown more growth than PHYINF. However, no fluctuation has seen in any of the indices.

5.2. Preliminary Results

The empirical findings of the present study start by summarizing the results of unit root tests. We perform the Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test to check the stationarity nature of the underlying variables and their order of integration as these are the prerequisites for any time series estimation. The choice of the use of both ADF and PP is motivated by their methodological differences. The ADF test parametrically correct the autocorrelation and heteroscedasticity in the residuals of error terms by incorporating augmented terms while in the PP test it is done by a nonparametric way by modifying the ADF statistics (Das, 2019, pp-326-327).

Table 1: Results of Unit Root Tests

		Augmented Dickey-Fuller Test		Phillips-Perron Test		
Variable's Name	Model Specification	at level	1st difference	at level	1st difference	Concluding Remark
IGI	Intercept	1.229	-6.616***	1.143	-6.224***	I(I)
PHYINF	Intercept & trend	0.716	-4.297**	0.626	-4.342***	I(I)
SOCINF	Intercept & trend	-3.096	-5.606***	-0.357	-5.606***	I(I)

Source: Author's computation
Note: *** and ** denote statistically significance at the 1% and 5% levels, respectively.

The results of the ADF and PP tests are reported in Table 1. The results show that the null hypothesis of the existence of a unit root for IGI, PHYINF, and SOCINF are not rejected at their level as the calculated t-values are not significant at 5% level. However, the null hypothesis of all the variables is rejected after taking their first differences indicating that all the variables are first difference stationary i.e., integrated of order one.

Once the stationarity nature of the variables is checked, the next step of the study is then to examine the long-run relationship between the variables using cointegration tests. Here, we used both the Engle Granger cointegration test and Johansen cointegration test to examine the long-run relationship among all underlying variables in this study. Our whole analysis is done in two parts. In the first, we apply bivariate models where

IGI is regressed separately on PHYINF and SOCINF and a multivariate model where IGI is regressed jointly on PHYINF and SOCINF. The nexus between IGI and PHYINF and between IGI and SOCINF are discussed in the next section.

5.2.1. Bivariate Analysis

In this section, we perform the Engle and Granger 2-stpe approach to cointegration (S between IGI and PHYINF and between IGI and SOCINF. First, we generate the residuals of the bivariate model (see equation 1) by applying ordinary least square method (OLS) and then ADF test is employed to test the stationarity nature of the residuals of the estimated cointegrating equations between IGI and PHYINF and between IGI and SOCINF:

$$IGI = 0.100 + 0.201PHYINF + 0.021t \quad (10)$$

$$IGI = 0.096 + 0.324\ SOCINF + 0.016t \quad (11)$$

Table 2: Results of Unit Root Test of estimated residuals between IGI and PHYINF and between IGI and SOCINF

Cointegration between IGI and PHYINF			
Augmented Dickey-Fuller Test at level			
Residual	t-statistics	p-value	variable's type
	-2.452	0.017	I(0)
Cointegration between IGI and SOCINF			
Residual	t-statistics	p-value	variable's type
	-2.374	0.020	I(0)

Source: Author's computation
Note: ** denotes the significance level at 5%.

The results (reported in Table 2) show that the residuals of both the models are stationary at their level as null hypothesis of no cointegration is rejected at 5% significance level. The results show that IGI and PHYINF are cointegrated in the long-run and a long-run equilibrium relationship may exist between them. The results also confirm the cointegration between IGI and SOCINF. Once the variables are cointegrated, one can analyze the long-run equilibrium relationship along with the short-run dynamics (reported in Table 3) by using the residuals of the cointegrating equations in an error correction model (ECM).

Table 3: Estimated Long-run relationship [Dependent variable: IGI]

Variables/Models	M1	M2
Constant	0.100*** (4.101)	0.096*** (3.798)
Trend	0.021*** (6.609)	0.016** (2.707)
PHYINF	0.201** (2.609)	-
SOCINF	-	0.324** (2.248)
R^2	0.959	0.956
Adj. R^2	0.955	0.952
AIC	-3.187	-3.124
SIC	-3.041	-2.978

Source: Author's computation
Note: In M1, PHYINF is the explanatory variable whereas, in M2, SOCINF is the explanatory variable.
*** and ** denote statistically significance at the 1% and 5% levels, respectively.
Figures reported in the first parenthesis are the t-values.

Granger causality test then can be applied to assess the direction of short-run causality between the variables. OLS is applied to estimate the long-run equilibrium relationship between IGI and PHYINF and between IGI and SOCINF. Equation M1 shows the estimated long-run relationship between IGI and PHYINF. It indicates that inclusive growth index increases by 0.20 points for every incremental point of physical infrastructure index to maintain the long-run equilibrium, *Ceteris peribus.* Similarly, Equation M2 indicates that inclusive growth index increases by 0.32 points for every incremental point of social infrastructure index to maintain the long-run equilibrium, *Ceteris peribus.*

Table 4: Results of Estimated Error Correction Model [Dependent Variable: D(IGI)]

Variables/Models	M1	M2
Constant	0.015 (1.885)	0.014 (1.389)
D(PHYINF)	0.213 (1.471)	-
D(SOCINF)	-	0.229 (1.091)
ECT $_{(-1)}$	-0.350** (-2.716)	-0.343** (-2.618)
R^2	0.269	0.246
Adj. R^2	0.199	0.174
AIC	-4.339	-4.308
SIC	-4.192	-4.161

Source: Author's computation
Note: In M1, D(PHYINF) is the explanatory variable whereas, in M2, D(SOCINF) is the explanatory variable.
** denotes statistically significance at 5% level. Figures reported in the first parenthesis are the t-values.

Thus, in the long-run, both physical and social infrastructure have a significant positive relation with inclusive growth in India. Time trend of both the equations are positive and significant and hence bear a positive relation with inclusive growth in the long-run.

Table 4 reports the estimated error correction model of M1 and M2. The results indicate that, there is no significant instantaneous effect of change of PHYINF and SOCINF on inclusive growth in the short-run. However, the coefficients of the ECT for both the models are negative and significant at 5% level. This indicates that the system will converge to its long-run equilibrium path whenever there induce any shock to the system with a speed of 35% for PHYINF and 34% for SOCINF, respectively.

We further assess the direction of causality between IGI and PFYINF and between IGI and SOCINF to find the interrelationship between them. We apply VAR based Granger causality (Granger, 1961) test and the results are reported in Table 5.

Table 5: VAR Granger Causality/Block Exogeneity Wald Tests

Direction of Causality	Chi-Square	Decision	Remarks
PHYINF $\rightarrow$ IGI	8.671***	Reject H_0	Causality
IGI $\rightarrow$ PHYINF	2.641	Cannot Reject H_0	No Causality
SOCINF $\rightarrow$ IGI	12.115***	Reject H_0	Causality
IGI $\rightarrow$ SOCINF	3.911**	Reject H_0	Causality

Source: Author's computation
Note: *** and ** denote statistically significance at the 1% and 5% levels, respectively.
Here, x $\rightarrow$ y means x is the cause of y.

The optimum lag length of the VAR model is one (see Table A3 in the Appendix) as suggested by Akaike information criterion (AIC), Schwarz information criterion (SIC), etc. Finally, we perform some diagnostic tests to check the goodness of the models. Results (see Table A4, A5 and Fig 2, 3 in Appendix) show that our model is free from serial correlation, normal and also stable. The results of causality tests indicate that physical infrastructure and social infrastructure cause inclusive growth in the short-run implying that other things remain the same, inclusiveness in growth can be achieved through the expansion of physical and social infrastructure. Causality also runs from inclusive growth to social infrastructure indicating the need of inclusiveness in growth for facilitating social infrastructure particularly, health and education infrastructure.

Overall. From the bivariate analysis, it is observed that physical and social infrastructure are cointegrated with inclusive growth and have a significant positive long-run relationship in India. The study also observed short-run unidirectional causality between physical infrastructure to inclusive growth and bidirectional causality between social infrastructure and inclusive growth.

The analysis of above said bivariate models may have some limitations as it uses single equation method to estimate the nexus between IGI, PHYINF, and SOCINF. The results of such analysis may be biased due to the omission of the other relevant variables or keeping them as constant either. To overcome this issue, the study further conducts a multivariate analysis to check the robustness of the estimated results. Unlike bivariate models, the multivariate model takes both PHYINF and SOCINF as the explanatory variables.

5.2.2. Multivariate Analysis

The multivariate analysis of the present study starts with testing the cointegrating relationship between IGI, PHYINF, and SOCINF. For this purpose, we employ Johansen Co-integration test (1988) to find the long run relationship among them. Table 6 reports the results of Johansen Co-integration test. Both Trace statistics (see Equation 3) and Max statistics (See Equation 4) indicate the existence of one cointegrating equation among the variables implying that IGI, PHYINF, and SOCINF are cointegrated. Cointegration indicates the existence of long-run equilibrium relationship between two or more non-stationary variables though it does not shed any light on the short-run forces that keep the long run relationship intact (Bhaumik, 2015, pp. 273).

Table 6: Results of Johansen Cointegration Test

No. of Co-integrating equations	Trace statistics	5%critical value	Max Eigenvalue Statistics	5%critical value
None*	35.616	29.797	24.745	21.131
At most 1	10.871	15.494	0.274	7.391

Source: Author's computation

Note: Both the Trace and Max-Eigen value tests indicate 1 cointegrating equation at the 0.05 level.

* denotes rejection of the hypothesis at the 0.05 level

Thus, to estimate the long-run equilibrium relationship along with the short-run dynamics, we employ vector error correction model (VECM). The VECM representation of the variables under study are presented in Equation 5. Before executing the VECM, the study determines the VAR optimum lag length for the model. Results suggest lag one as the optimum lag length for the study (see, Table A3 in the Appendix).

Table 7: Estimated Long Run Relationship

Variable	Coefficient	Std. Error	t-statistics
IGI (-1)	1.000		
PHYINF (-1)	-1.535***	0.270	-5.681
SOCINF (-1)	-2.989***	0.474	-6.299
Trend	-0.083***	0.009	-8.679
Constant: -0.114			

Source: Author's computation

Note: *** denotes the significance level at 1%.

The results of estimated long run relationship between IGI, PHYINF, and SOCINF are reported in Table 7. The long-run equilibrium relationship between IGI, PHYINF, and SOCINF is:

$$IGI = -0.114 + 1.535PHYINF + 2.989SOCINF - 0.083t \qquad (12)$$

Equation (8) indicates that inclusive growth increases 1.535 point for every incremental one point of physical infrastructure and 2.989 points for every incremental one point of social infrastructure in the long-run. Thus, the results indicate a positive long-run association between inclusive growth, physical infrastructure and social infrastructure and in line with our bivariate results. The short-run ECM is reported in Table 8. Unlike bivariate analysis, the multivariate results find a short-run association between IGI, PHYINF, and SOCINF. In the short-run, the change of physical infrastructure and social infrastructure have a significant effect on the change of inclusive growth. The coefficient of the error correction term is negative and significant indicating that the process will converge towards its long-run equilibrium value at a speed of 22% whenever there induce any short run disturbance in the system. Lastly, we perform some diagnostic test to check the validity of the VECM using LM test, J-B test, and CUMSUM of square test. The results (see the Table A6, A7 and Fig. 4) indicate that the model is valid as it is normal, stable and free from serial correlation.

Table 8: Results of Estimated Error Correction Model [Dependent Variable: D(IGI)]

Variable	Coefficient	Std. Error	t-statistics
D (IGI (-1))	0.007	0.128	0.006
D (PHYINF (-1))	0.238*	0.126	1.881
D (SOCINF (-1))	0.452**	0.209	2.158
ECT (-1)	-0.226***	0.07	-3.207
Constant	-0.006	0.010	-0.063

Source: Author's computation
Note: ***, **, and * denotes the significance level at 1%, 5%, and 10% level, respectively.

Finally, the study performs the Granger causality test in the vector error correction model (VECM) to assess the direction of causality as the cointegration does not indicate the causal direction. Knowing the direction of causality between IGI, PHYINF, and SOCINF would be vital for the policy makers to formulate appropriate infrastructural policies for promoting inclusiveness in growth. Table 9 reports the results of causality test. The results of the short-run Granger causality test indicate that Physical and social infrastructure causes inclusive growth as causality runs from both the infrastructures to inclusive growth. However, no causality runs from inclusive growth to any of the infrastructures. The causality results in VECM are also in line with the causality results of that based on the VAR framework.

Table 9: VECM Granger Causality Tests

Direction of Causality	Chi-Square	Decision	Remarks
PHYINF → IGI	3.541*	Reject H_0	Causality
IGI → PHYINF	1.389	Cannot Reject H_0	No Causality
SOCINF → IGI	4.658**	Reject H_0	Causality
IGI → SOCINF	0.348	Cannot Reject H_0	No Causality
SOCINF → PHYINF	3.975**	Reject H_0	Causality
PHYINF → SOCINF	0.823	Cannot Reject H_0	No Causality

Source: Author's computation
Note: ** and * denote statistically significance at the 5% and 10% levels, respectively.
Here, x → y means x is the cause of y.

Our empirical findings of both bivariate and multivariate models are in line with the empirical evidences of Mutiiria et al. (2020) who found a positive link between transport infrastructure, ICT infrastructure and inclusive growth in the sub-Saharan Africa. Our empirical findings also support the view of Anand et al., (2013), Kanbur and Rauniyar (2010), ADB (2012), Bhattacharya et al., (2020), etc. that expansion of infrastructural facilities can promote inclusive growth.

VI. CONCLUSION

This study explored the nexus between inclusive growth and infrastructure namely, physical and social infrastructure for India over the period 1991 to 2015. The study constructed inclusive growth index (IGI) considering 8 developmental indicators as its components (categorized into economic expansion, environmental sustainability, gender equity, human development, and financial inclusion), physical infrastructure index (PHYINF) based on transport, power, and telecommunication infrastructure indicators and social infrastructure index (SOCINF) based on education and health infrastructure indicators. In order to construct the indices, the study employed weighted average method (It assigns equal weight to each of the indicator within a dimension). The calculated indices are then used to test the nexus between IGI, PHYINF, and SOCINF based on a bivariate and a multivariate framework. The results of bivariate analysis are quite similar to that of multivariate analysis indicating the stability of the robustness of the estimated models. The empirical findings of the study can be summarized as follows: Firstly, all the variables i.e., IGI, PHYINF, and SOCINF are cointegrated in the long-run. Cointegration is also found between IGI and PHYINF and between IGI and SOCINF. Secondly, both PHYINF and SOCINF possess significant positive long-run equilibrium relationships with inclusive growth in the long-run. Thirdly, a short-run relationship is also found between IGI, PHYINF, and SOCINF where the change of PHYINF and SOCINF positively affect the change of IGI. In addition, Granger causality test based on both the VAR and VECM framework reveals that PHYINF and SOCINF unidirectionally cause IGI though the causality can be seen from both the direction between SOCINF and IGI when analyzing them in a bivariate framework. A causal relation is also seen between PHYINF and SOCINF where the causality runs from SOCINF to PHYINF.

From the policy suggestion, the findings of the study conclude that to promote greater inclusiveness and ensuring sustainability in all sphere, appropriate developmental policies for increasing access and affordability of basic infrastructural services are highly recommended. This study makes an attempt to provide empirical evidences on the role of infrastructure in growth inclusiveness. Earlier, attempts have been made to quantify the role of infrastructure in promoting inclusiveness but none of the study clearly provides strong empirical evidences on this nexus. It is, however, relatively well established that infrastructure can promote inclusive growth which in turn will reduce poverty directly and indirectly (ADB, 2012). The results of our study also justify this. In this context, this study makes a significant contribution in the emerging inclusive growth literature.

VII. LIMITATIONS AND SCOPES FOR FURTHER RESEARCH

This study has its own limitations. While analyzing the impact of different sub-sectors of infrastructure on inclusive growth, this study did not consider financial infrastructure due to its limited data. Secondly, the present study used indexed variable for this analysis. However, using indexed variable may ignore the actual effect of the individual indicators and hence lead to fallacious conclusion. Thirdly, the results of the present study are limited to a specific country and could not capture the impact of infrastructure on reginal or cross-country level which is very important for policy formation. Lastly, the present study took only infrastructure as its determining factor and analyzing its impact on inclusive growth though literature suggested several factors like foreign direct investment (FDI), trade openness, inflation, exports, good governance, etc. which have significant effect on inclusive growth in a country. Considering these limitations, researchers can explore cross-country level analysis to assess the impact of different factors of inclusive growth. Secondly, they can also explore the role of financial infrastructure, particularly digital infrastructure, in inclusive growth. Lastly, the role of different individual infrastructural indicator in inclusive growth can also be examined which may help policy makers to formulate effective infrastructural polices for promoting greater inclusiveness in growth.

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Appendix

Table A.1: Data source and Indicators of Inclusive Growth

Dimension	Indicators	Sources	Ad hoc Weights attached to the indicators
Economic Inclusion	Per capita GDP Rupees	Hand book of statistics of Indian economic, RBI	0.125
	Employment to population ratio, 15+, male (%) (modelled ILO estimate)	World Development Indicators, World Bank Database;	0.125
Environmental Sustainability	CO_2 emissions (metric tons per capita)	World Development Indicators, World Bank Database;	0.125
Gender Empowerment	Number of Female per hundred Male Enrolled in Primary education	Education Statistics of India, various years- MHRD, GoI	0.125
Human Capability	Mortality rate, infant (per 1,000 live births)	Health Statistics of India, Ministry of Health and Planning Various Years, GoI.	0.125
	School enrolment, primary (% gross)	World Development Indicators, World Bank Database	0.125
Financial Inclusion	C/D ratio (%)	Hand Book of Statistics, RBI – Banking Statistics	0.125
	Number of bank account per 100000 populations	Hand Book of Statistics, RBI -Banking Statistics	0.125

Table A.2: Data source and Indicators of Infrastructure

Dimension	Sub-Dimension	Indicators	Sources	Ad hoc Weights attached to the indicators
Physical Infrastructure	Transport Infrastructure	Road density (Road length per 1000 sq. kms areas)	Centre for Monitoring Indian Economy (CMIE) data base	0.25
		Rail density (Railway route length per 1000 sq. kms areas)	Centre for Monitoring Indian Economy (CMIE) data base	0.25
	Telecommunication Infrastructure	Tele-density (per 100 subscribers, base by GSM, CDMA, and Wireline users)	Centre for Monitoring Indian Economy (CMIE) data base	0.25
	Power Infrastructure	Installed Plant Capacity, Utilities (MW), per 10,000 people	EPWRF India time series	0.25
Social Infrastructure	Education Infrastructure	Total Number of all schools, per 1000 sq. kms areas	EPWRF India time series; Education Statistics of India, various years- MHRD, GoI	0.167
		Total Number of Colleges, per 1000 sq. kms areas	EPWRF India time series; Education Statistics of India, various years- MHRD, GoI	0.167
		Universities (Number) per 10,000 sq. kms areas	EPWRF India time series; Education Statistics of India, various years- MHRD, GoI	0.167
	Health Infrastructure	Doctors registered with Medical Council of India/ State Medical Councils, per 10,0000 people	EPWRF India time series	0.167
		Registered Nurses and Registered Midwives (RN & RM), per 100000 people	EPWRF India time series	0.167
		Physical Health Centre (PHC): In Numbers, per 1000 sq. kms areas	EPWRF India time series	0.167

Table A.3: VAR Lag Order Selection Criteria

Lag	LR	FPE	AIC	SIC	HQ
0	NA	0.000633	-1.689823	-1.591084	-1.664990
1	160.4153*	2.95e-07*	-9.362763*	-9.066547*	-9.288265*
2	4.284455	3.33e-07	-9.252962	-8.759269	-9.128799

Source: Authors' computation
Note: (*) indicates lag order selected by the above criterion

Table A.4: Results of Breusch-Godfrey Serial Correlation LM Test

Model 1		
F-statistic	Probability	Decision
0.833	0.960	No serial correlation
Model 2		
1.065	1.213	No serial correlation

Source: Author's computation.

Table A.5: Results of Jarque-Bera Normality Test

Model 1		
F-statistic	Probability	Decision
0.262	0.876	Normal
Model 2		
0.375	0.829	Normal

Source: Author's computation.

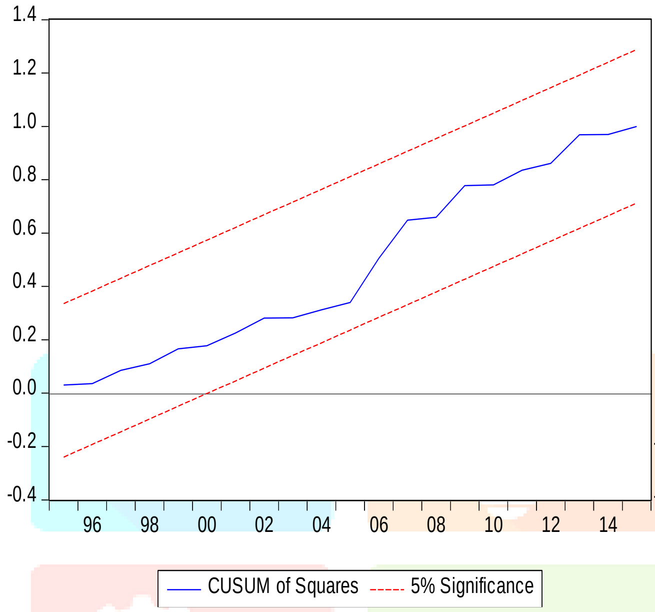

Figure A2. CUSUM Test for Model Stability of Model 1

Source: Author's computation.

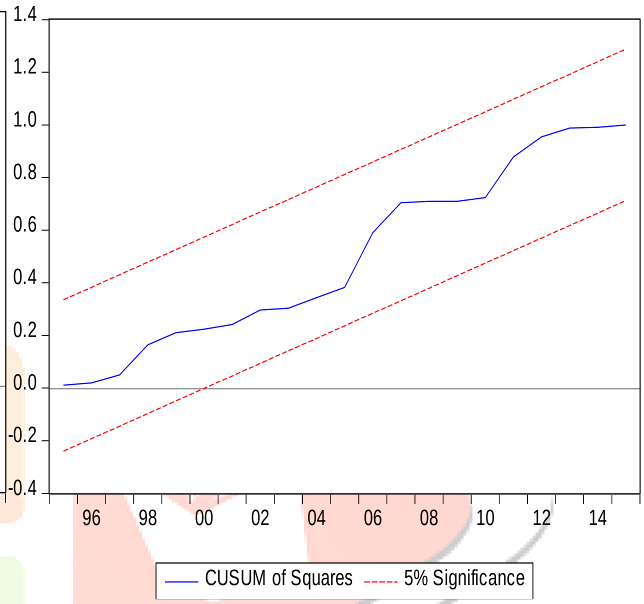

Figure A3. CUSUM of Squares Test for Model Stability of Model 2

Source: Author's computation.

Table A.6: Results of Breusch-Godfrey Serial Correlation LM Test

F-statistic	Probability	Decision
0.012	0.913	No serial correlation

Source: Authors' computation.

Table A.7: Results of Jarque-Bera Normality Test

F-statistic	Probability	Decision
0.026	0.987	Normal

Source: Authors' computation.

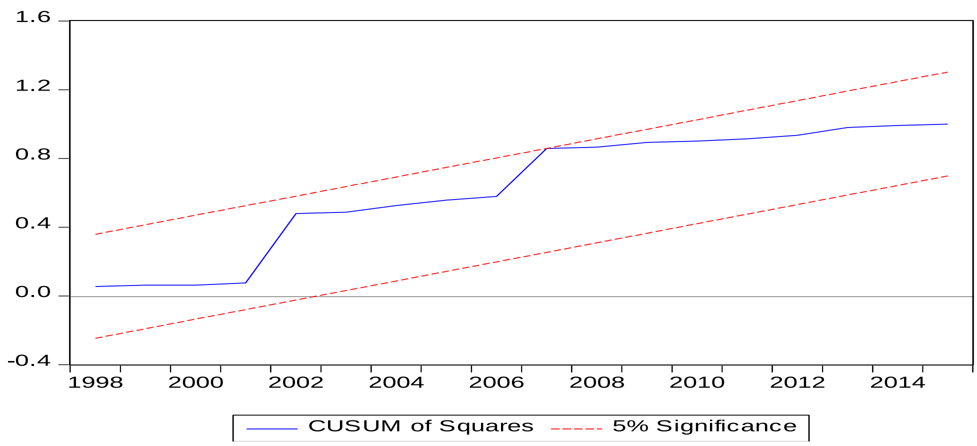

Figure A4. CUSUM of Squares Test for Model Stability o

Source: Authors' computation.