Rural Public Expenditure and Poverty Alleviation in India: A Spatial Econometric Analysis

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Abstract
In India, a pivotal strategy for poverty reduction involves consistent and substantial public financial investments. This study utilizes spatial econometrics to analyse the structural disparities between rural public expenditures (including education, health, social security, infrastructure, and living environment) and poverty in India spanning from 2000 to 2020. The findings underscore notable variations in the poverty reduction impact of government spending. Expenditures on education, healthcare, social security, and infrastructure demonstrate positive effects on poverty alleviation, while spending on the living environment lacks significant impact on poverty reduction. Moreover, the study reveals that government spending not only facilitates poverty reduction in specific regions but also positively influences economically and geographically similar areas. This study suggests that the need for future research to explore in-depth how the effectiveness of government spending in reducing poverty varies based on its structural components. Consequently, the insights gleaned from this research hold substantial implications for shaping targeted poverty alleviation measures in India through well-informed government spending policies.

Keywords: Education, Health, Government Expenditure, Poverty Alleviation, Econometrics

INTRODUCTION

In the context of India, the intersection of rural public expenditure and poverty alleviation represents a critical nexus that has profound implications for the well-being of its rural population. As a country characterized by a significant rural demographic, effective public spending in rural areas plays a pivotal role in addressing and mitigating poverty. This introduction aims to explore the intricate relationship between the allocation of public funds in rural development initiatives and the overarching goal of poverty alleviation. By delving into the specific mechanisms, policies, and strategies implemented in India, we can unravel the impact of public expenditure on the lives of those residing in rural communities, shedding light on the challenges, successes, and potential avenues for improvement in the ongoing pursuit of poverty reduction. The global community has consistently shown deep concern for poverty eradication, particularly in developing nations Bapna, (2012). Governmental social welfare initiatives play a pivotal role in influencing poverty alleviation, addressing economic and political rights distribution. The cyclical process of poverty reduction in developing countries involves implementing political, economic, and educational policies to narrow the gap between the affluent and the impoverished Pater, et al., (2008). India and China, both economically underdeveloped countries with large populations, actively pursue policies to alleviate poverty, particularly through rural poverty alleviation programs. While China is dedicated to its own poverty eradication, it collaborates with other developing nations to support their poverty reduction efforts, making substantial contributions to global poverty reduction Liu, et al., (2017). Despite significant achievements, particularly driven by urbanization, India faces a stark rural-urban welfare divide. Rapid economic growth and commitment to poverty eradication have improved India's overall economic landscape. However, the uneven rural development persists, highlighting challenges in the formulation of anti-poverty policies Mooij & Dev, (2004). Given the substantial

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rural populations in both China and India, the study of rural poverty causes and government policies in these countries can offer valuable lessons for global poverty alleviation and narrowing the global wealth gap Zou, (2012). Numerous scholars have delved into rural anti-poverty policies in India; however, few have presented comparative analyses of these policies in India. This paper aims to fill this gap by reviewing the literature on rural poverty and pro-poor policies in both countries, subsequently analyzing and discussing the pro-poor policies in India. Regarding rural poverty in China, Feng et al. (2017) attribute it to unequal land holdings and exploitative relationships, pointing out that the collectivization system limits peasants' productive incentives. Technological constraints in production also hinder agricultural development, leading to increased labor inputs without commensurate benefits Feng et al., (2017). In India, empirical evidence from studies like Huan et al. (2022) demonstrates that economic growth, inclusive poverty reduction programs, and improved public services significantly contribute to poverty reduction. Growth patterns matter, with rural growth impacting poverty reduction approximately four times more than non-agricultural growth Ravallion & Chen, (2007). Fan et al. (2000) and Qin and Zhang (2022) highlight the positive impact of government investment on poverty reduction in rural India, attributing it to agricultural sector growth, increased agricultural wages, and non-agricultural employment opportunities. Exploring the factors contributing to rural poverty, researchers have examined anti-poverty policies in India. Fan et al. (2000) found that investments in rural roads and agricultural research had a greater impact on poverty reduction and productivity growth than other government investments, indicating the positive role of public spending. However, Breitkreuz et al. (2017) suggest that the Mahatma Gandhi National Rural Employment Guarantee Scheme, while impacting short-term income growth, has limited long-term impact on marginalized populations. Singh and Chudasama (2020) advocate for a multidimensional approach, emphasizing the need for integrated efforts in poverty alleviation. Recognizing the plethora of studies on rural public expenditure and poverty alleviation, this paper undertakes an econometric analysis to address the gap in effective utilization of these methods. The subsequent sections are organized into an introduction and literature review, research methodology, presentation and discussion of results, conclusion, and policy recommendations.

RESEARCH METHODOLOGY

Data types and sources:

This research exclusively utilized secondary data, drawing information from reputable sources such as the World Development Indicator, the Indian Economic Survey, and the Handbook of Statistics. The study covered a substantial time frame, spanning two decades from 2000 to 2020.

Table 1: Variable names and description

Variable Name	Log Form	Description (Proxy Variable)	Sources
Poverty head count ratio	LNPOV	Poverty headcount ratio at $6.85 a day (2017 PPP) (% of population)	World Bank
Eductaion	LNEDU	Adjusted savings: education expenditure (% of GNI)	World Bank
Health	LNHEL	Rural Health expenditure	WDI
Social Contribution	LNSS	Social contributions (% of revenue)	World Bank
Infratsturate	LNINFR	Access to electricity, rural (% of rural population)	World Bank

European Economic Letters
ISSN 2323-5233
Vol 14, Issue 2 (2024)
http://eelet.org.uk

Environmental	LNENV	CPIA policy and institutions for environmental sustainability rating (1=low to 6=high)	WDI

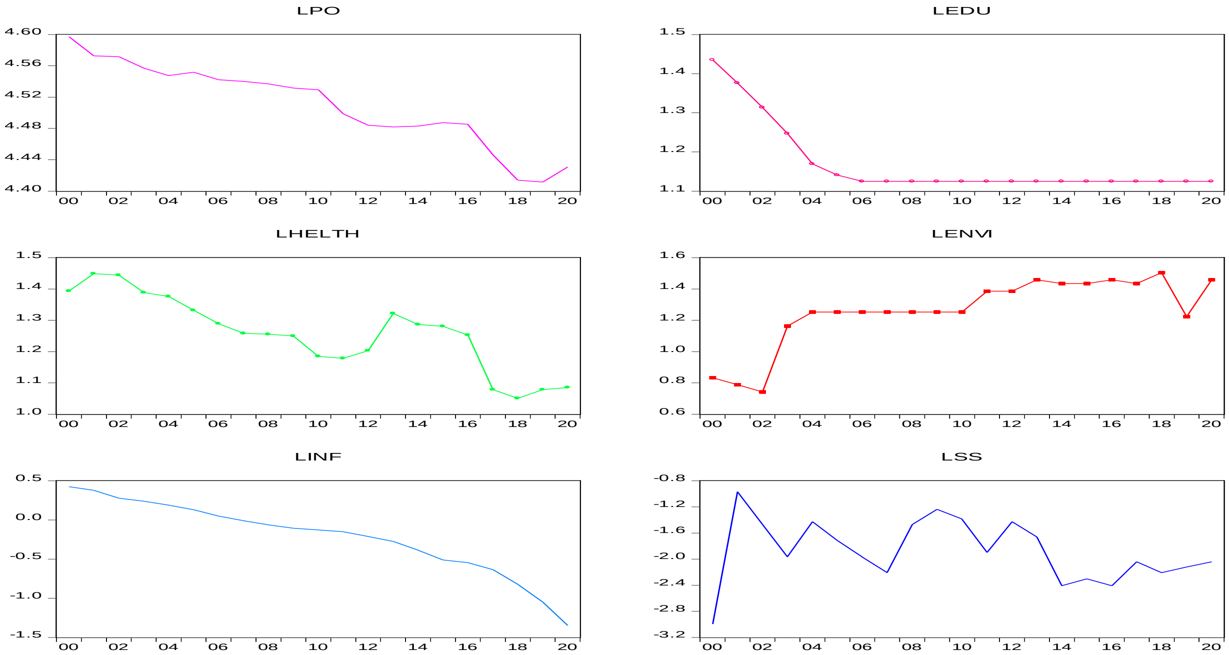


Figure 1, Trends

Econometric Model:

This study econometric model is as follows:

$POV = \beta 0 + \beta 1\ (EDU) + \beta 2\ (HEL) + \beta 3\ (SS) + \beta 4\ (INF) + \beta 5\ (ENV) + \mu$ …… 1

In the context of this study:

POV represents the Poverty Rate, EDU stands for Education., HEL represents Health, SS corresponds to Social Security, INF denotes Infrastructure, ENV refers to the Environment, In the regression model, $\beta 0$ signifies the intercept, $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$, $\beta 5$ are the coefficients associated with Education, Health, Social Security, Infrastructure, and Environment, respectively. The error term is represented by μ.

Autoregressive Distributed Lag Model:

The ARDL (Autoregressive Distributed Lag) technique has been utilized to explore the connection between rural expenditure and poverty alleviation. Introduced by Pesaran et al. (1996), and Pesaran and Shin (1999), the ARDL bounds testing technique is versatile, necessitating that the variables in the model specification be integrated at order 0 or 1, denoted as I(0) or I(1). This approach is robust even with small sample sizes, offering reliable results. Variables in the model can be assigned different lag lengths to capture various dynamics. The ARDL equation takes the form:

$Yt=\beta 0+\beta 1\ Yt-1+\ldots\beta q\ Yt-P + \alpha 0\ Xt+\alpha 1Xt-1+\alpha 2Xt-2+\ldots\alpha kXt-k+\varepsilon t$ …………2

Notably, this technique has been recently employed by several researchers, reflecting its applicability and relevance in contemporary studies (Ansari, et, al., 2022; Ansari, et, al., 2022; Ansari, et, al., 2023; Ansari, et, al., 2023; ; Amir, et, al., 2023; Amir, et, al., 2024; Khan, et, al., 2023; Rashid, et, al., 2023; Rehmat at. al., 2023)

The unconstrained vector error model, on the other hand, is shown below

$$\Delta POV_t = \gamma_0 + \sum_{I=1}^{P} \gamma_1 \, POV_{t-1} + \sum_{I=1}^{P} \gamma_2 \, EDU_{t-1} + \sum_{I=1}^{P} \gamma_3 \, HEL_{t-1} + \sum_{I=1}^{P} \gamma_4 \, SS_{\,t-1} + \sum_{I=1}^{P} \gamma_5 \, INFR_{t-1} + \sum_{I=1}^{P} \gamma_6 \, ENVIR_{t-1} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots 3$$

The ARDL model, shown in Equation (3), demonstrates the long-run and short run connection between the dependent and independent variables. The intercept term is 0. The short-run coefficients of variables are γ0, γ1 γ2, γ3, γ4, γ5, γ6, explanatory variables, whereas the long run coefficients of variables , and t is the stochastic error, which includes all missing variables in the equation.

Short-Run Relationship Error Correction Model

This approach determines the short-run relationship between the GDP and other independent variables. The following is the short-run error correction equation:

$$\Delta POV_t = \partial_0 + \sum_{I=1}^{P} \partial_{1i} \, POV_{t-1} + \sum_{I=1}^{P} \partial_{2i} \, EDU_{t-1} + \sum_{I=1}^{P} \partial_{3i} \, HEL_{t-1} + \sum_{I=1}^{P} \partial_{4i} \, SS_{\,t-1} + \sum_{I=1}^{P} \partial_{5i} \, INFR_{t-1} + \sum_{I=1}^{P} \partial_{6i} \, ENVIR_{t-1} + \lambda(ECM)t\text{-}i + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots 4$$

(ECM-i) The ECM illustrates the short-run influence on the x and y variables and the adjustment rate.

$$\Delta Yt = \eta + \delta t\text{-}i + \lambda(ECMT\text{-}I) + \mu t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 5$$

In the equation, (δ) denotes the short-run effect and (λ) denotes the adjustment speed. Table 6 displays the ECM findings.

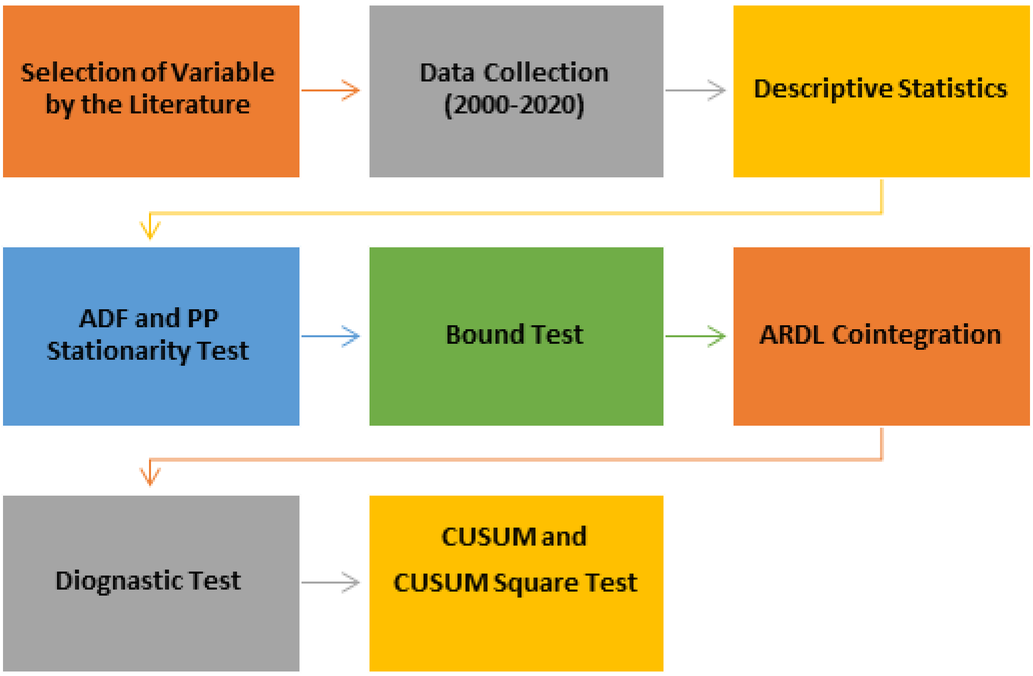


Figure 2 framework of Model

RESULT AND DISCUSSION

Table 1: Descriptive Statistics of Dependent and Independent variable

	LPO	LEDU	LHELTH	LENVI	LINF	LSS
Mean	4.51	1.17	1.26	1.26	-0.22	-1.87

Median	4.53	1.12	1.26	1.25	-0.13	-1.97
Maximum	4.6	1.44	1.45	1.5	0.43	-0.97
Minimum	4.41	1.12	1.05	0.74	-1.35	-3
Std. Dev.	0.05	0.09	0.12	0.22	0.47	0.48
Skewness	-0.38	1.93	-0.21	-1.25	-0.77	-0.22
Kurtosis	2.18	5.3	2.16	3.61	2.97	2.79
Jarque-Bera	1.11	17.7	0.77	5.8	2.07	0.21
Probability	0.57	0	0.68	0.06	0.35	0.9
Observations	21	21	21	21	21	21
Correlation						
LPO	1					
LEDU	0.64	1				
LHELTH	0.87	0.67	1			
LENVI	-0.74	-0.88	-0.69	1		
LINF	0.95	0.6	0.85	-0.69	1	
LSS	0.24	-0.04	0.21	-0.22	0.3	1

Source: Auther's calculate Eview-10

Table 1 displays the average growth rate of LPO at 4.51%, with a standard deviation of 0.05%. The mean value for education (LEDU) is 1.17, accompanied by a standard deviation of 0.09. LHELTH registers an average of 1.26 with a standard deviation of 0.12, while LENVI maintains a mean of 1.26 and a standard deviation of 0.22. LINF exhibits a mean of -0.22, accompanied by a standard deviation of 0.47, and LSS has a mean value of -1.87, with a standard deviation of 0.48. Skewness is evident in all variables except EDU, including LPOV, HEL, LENVI, LINF, and LSS. Kurtosis statistics reveal that LPO, LHEL, LINF, and LSS are platykurtic (short-tailed) as their values are less than 3, while LEDU and LENVI are leptokurtic (long-tailed) with values exceeding three.

The Jarque-Bera P-values for LEDU and LENVI are 0.00 and 0.06, respectively, the latter being less than 10%, leading to the rejection of the null hypothesis, suggesting non-normal distribution. Conversely, the Jarque-Bera P-value for LPO is 0.57, exceeding 10%, leading to the acceptance of the null hypothesis, indicating normal distribution. Thus, as the Jarque-Bera P-values for all other variables surpass 10%, the null hypothesis is accepted, indicating a normal distribution for those variables.

In Table 1, also the correlation between the dependent and independent variables is evident, except for LENVI, which shows a strong negative association with LPO. Notably, LPO exhibits strong positive correlations with LEDU, LHEL, LINF, and LSS.

PP and ADF Test Results Table 2

UNIT ROOT TEST TABLE (ADF)							
At Level				**At First Difference**			
Variable	**t-Statistic**	**Prob.**	**Decision**	**Variable**	**t-Statistic**	**Prob.**	**Decision**
LPO	-4.38	0.00	**I(0)**	**d(LPO)**	-2.76	0.00	I(I)
LEDU	-0.21	0.59	**n0**	**d(LEDU)**	-12.58	0.00	I(I)
LHELTH	-1.3	0.16	**n0**	**d(LHELTH)**	-3.52	0.00	I(I)
LENVI	0.93	0.89	**n0**	**d(LENVI)**	-4.92	0.00	I(I)
LINF	1.61	0.96	**n0**	**d(LINF)**	1.26	0.94	I(I)
LSS	-1.17	0.21	**n0**	**d(LSS)**	-8.31	0.00	I(I)
UNIT ROOT TEST TABLE (PP)							
At Level				**At First Difference**			

Variable	t-Statistic	Prob.	Decision	Variable	t-Statistic	Prob.	Decision
LPO	-4.04	0	**I(0)**	d(LPO)	-2.79	0.01	I(I)
LEDU	-1.76	0.07	**I(0)**	d(LEDU)	-2.01	0.05	I(I)
LHELTH	-1.28	0.18	**n0**	d(LHELTH)	-3.52	0.00	I(I)
LENVI	1.05	0.92	**n0**	d(LENVI)	-4.92	0.00	I(I)
LINF	2.25	0.99	**n0**	d(LINF)	-4.26	0.00	I(I)
LSS	-1.16	0.22	**n0**	d(LSS)	-13.89	0.00	I(I)

Source: Auther's calculate Eview-10

Table 2 shows thatt the stationary and non-stationary characteristics of the variables, a critical consideration in time series data for precise regression analysis and dependable forecasts. Both the PP and Augmented Dickey-Fuller tests reveal that some variables are stationary at the level, while others necessitate first-order differencing. Time series analysis indicates distinct integration orders for all variables, implying the absence of co-integration, thereby permitting the utilization of the ARDL model (Ansari, et al., 2023; Khan, et al., 2024). The bound test for co-integration serves to unveil the long-term relationships between the variables, and the results are presented in Table 3.

Bound Test Results Table 3

Test Statistic	Value	Significance.	I(0)	I(1)
F-statistic	5.958	10%	1.81	2.93
k	5	5%	2.14	3.34
		2.50%	2.44	3.71
		1%	2.82	4.21

Source: Auther's calculate Eview-10

The critical values for the upper and lower bounds, denoted as I(1) and I(0), are provided in the aforementioned table. Given that the observed F-statistics value surpasses the upper bound of F-Statistics, we reject the null hypothesis and consequently embrace the alternative hypothesis. This alternative hypothesis posits a long-term connection between the variables.

The ARDL Model's Long-Term Relationship

The long term relationship between the dependent and independent variables is expressed as an equation.

Table 4 the long-term relationship in Dependent and Independent variable

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEDU	5.927	1.48	4	0
LHELTH	3.127	1.65	-1.89	0.1
LINF	0.905	0.37	2.42	0.04
LENVI	-1.478	0.42	3.5	0.01
LSS	0.007	0.13	0.06	0.96

Source: Auther's calculate Eview-10

Table 4 displays the outcomes of the ARDL model, highlighting the substantial and positive long-term impact of LEDU on LPO. A 1% increase in LEDU corresponds to a 5.92% rise in LPO. This aligns with previous research indicating varied effects based on the nature of spending—direct impacts (e.g., social security) and indirect effects (e.g., health, education, infrastructure) (Wang & Liu, 2016; Anderson, 2018). Rural infrastructure investment, social security, and health and education expenditures are identified as effective means for poverty reduction (Fan et al., 2005; Benjamin et al., 2005; Gomanee & Morrissey, 2002; Oluwatobi & Ogunrinola, 2011). However, fiscal expenditure on education may not significantly reduce poverty, unlike health care in Bangladesh (Asadullah et al., 2014). LHELTH positively and significantly impacts LPO at 10%, while LINF exhibit positive and significant effects. LSS, while positive, lacks statistical significance in poverty alleviation. This study aligns with research on public expenditure's role in agricultural growth and poverty reduction (Fan et al., 2005, 2007). Spatial correlation in public expenditure's poverty reduction effect is considered, involving issues like spatial spillover and difference (Gong et al., 2018; Zou, 2014; Deng et al., 2015). Gong et al. (2018) particularly focused on rural public spending.

Table 5, Short-Run Relationship Error Correction Model

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(LEDU)	0.2	0.07	-2.73	0.03
D(LHELTH)	0.04	0.03	1.53	0.16
D(LINF)	0.06	0.01	4.71	0
D(LENVI)	-0.02	0.01	-1.28	0.24
D(LSS)	0	0	-0.53	0.61
CointEq(-1)*	-0.06	0.01	7.62	0

Author's calculation based on Eviews-10

According to the information presented in Table 5, it is evident that education emerges as the most influential variable both in the long and short run. The ECM (Error Correction Model) coefficient, registering at -0.06, is not only negative but also statistically significant. This substantial and negative ECM coefficient signifies a long-term causal relationship. The ECM value indicates the speed at which the system adjusts from disequilibrium to equilibrium.

Table 6, Model of summary

R-squared	0.875	Mean dependent var	-0.010
Adjusted R-squared	0.826	S.D. dependent var	0.013
S.E. of regression	0.005	Akaike info criterion	-7.360
Sum squared resid	0.000	Schwarz criterion	-7.061
Log likelihood	75.916	Hannan-Quinn criter.	-7.309
Durbin-Watson stat	2.473		

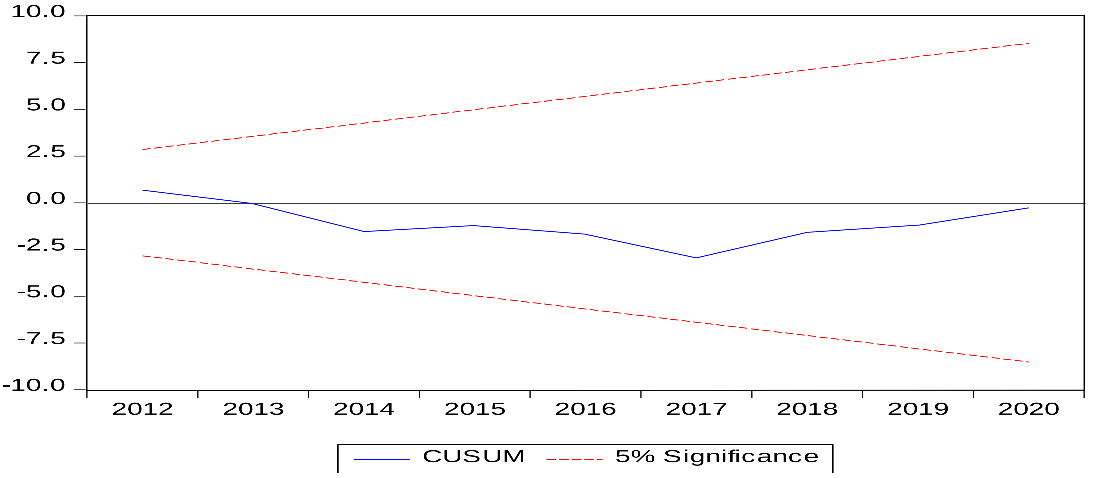
Author's calculation based on Eviews-10

Table 6, the corrected R-square, standing at 0.875, indicates that approximately 87.5% of the variance in poverty alleviation (the dependent variable) can be attributed to changes in independent factors. This reflects a high explanatory power of the model. Additionally, the likelihood of the F-statistic is statistically significant at the 5% level, affirming the model's goodness of fit.

Model Stability:

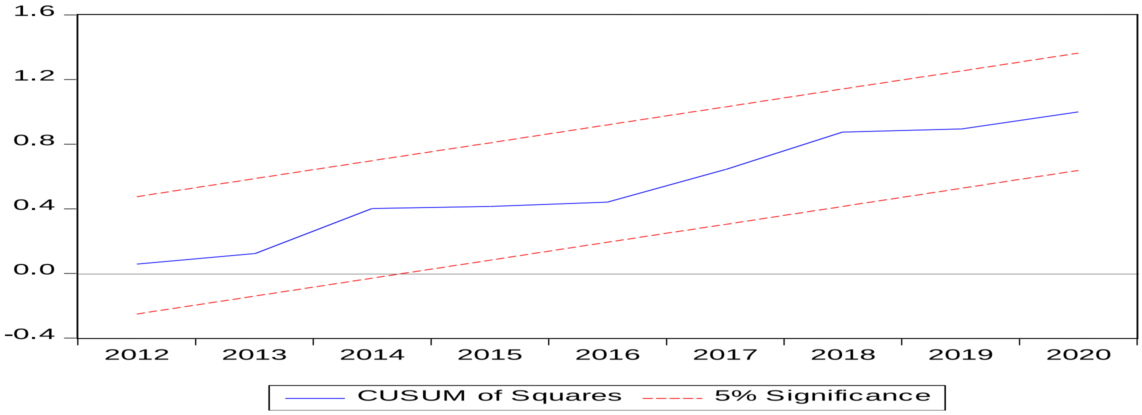
The Cumulative Sum of Recursive Residuals (CUSUM) serves as an indicator of the model's stability concerning both short and long-term relationships between variables. The graph depicting the cumulative total of the recursive residuals is presented below.

Figure 3, CUSUM test



Author's calculation based on Eviews-10

Figure 4, CUSUM square Test



Author's calculation based on Eviews-10

Figure 3, and figure 4, The CUSUM and CUSUM square test assesses the stability of the model by plotting the time series on the horizontal axis and residuals on the vertical axis. As depicted in Figure 1, the CUSUM stays within the 5% critical line range, indicating that it does not breach this crucial threshold. Consequently, we can deduce that the model is stable, and there are no significant deviations. At the 5% significance level, this well-specified model lends support to the null hypothesis.

CONCLUSION

This study delves into the repercussions of rural government expenditure on poverty in India spanning from 2000 to 2020, scrutinizing five dimensions: education (EDE), health (HEE), social security (SOE), infrastructure (INFE), and living environment (EVNE). Employing the ARDL model, it identifies nuanced disparities in the poverty reduction effects of these expenditures, discerning between their enduring and immediate impacts. The key findings underscore substantial differences in the poverty reduction effects of government spending across these five dimensions.

While education, healthcare, social security, and infrastructure expenditures manifest positive impacts at the national level, the expenditure on the living environment does not significantly contribute to poverty reduction.

IMPLICATION OF POLICY

In terms of policy implications, a pivotal consideration is augmenting the government's role in poverty reduction through targeted adjustments in public expenditure. Prioritizing key areas, such as education, healthcare, social security, and infrastructure, where expenditures demonstrate substantial poverty reduction effects, can significantly enhance the government's impact. Concurrently, addressing external factors, including investments in the living environment, the advancement of rural human settlements, and the promotion of green services, can contribute further to poverty alleviation.

This study also highlights discernible spatial spillover effects related to various rural government expenditures and poverty. Notably, expenditures in education, health, social security, and infrastructure not only contribute to poverty reduction within a specific region but also extend their benefits to economically and geographically similar areas. Conversely, the impact of living environment expenditure on poverty reduction is found to be insignificant for the area and its counterparts. Future research should delve deeper into regional variations in the effects of government spending on poverty. It is recommended to undertake a comprehensive examination, leveraging spatial spillover effects to coordinate policies and actions between regions, thereby systematically addressing regional poverty challenges.

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