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Unraveling the Public Spending-Inclusive Growth Nexus: A PCA-GMM Analysis in Developing Economies

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ABSTRACT

This paper examines the intricate relationship between public spending and inclusive growth in developing economies, employing a novel multidimensional framework. The Author utilizes principal component analysis (PCA) to construct a robust measure of inclusive growth encompassing key drivers like education, health, income distribution, and environmental sustainability. Subsequently, generalized method of moments (GMM) estimates the causal impact of public spending on this newly-defined proxy.

Key findings reveal that targeted investments in education, health, and public goods positively enhance inclusive growth dimensions. Conversely, high unemployment rates pose a substantial obstacle to achieve inclusiveness. These results highlight the complex nexus between different types of public spending and their differential impact on fostering an inclusive growth environment.

Keywords: Inclusive Growth, Public Spending, GMM, PCA

1. Introduction

While rapid economic growth has long been seen as the engine of development, recent years have witnessed a growing focus on ensuring that this growth benefits the majority. This concept, known as inclusive growth, has become a major aspect for policymakers and economists seeking to build fair and sustainable societies.

Despite the widespread acknowledgment of the significance of inclusive growth, defining inclusive growth remains a complex undertaking. International organizations like the World Bank, IMF, UNDP, ADB, and WEF offer diverse perspectives, highlighting aspects such as pace and patterns of growth, reduced inequality, or environmental impacts [1]. Consequently, Challenges emerge in capturing multidimensional elements like poverty reduction, social equality, and environmental impact alongside traditional economic indicators [3] [4]. The paper reaches to a plausible definition for Inclusive growth driven from literatures, it is a process of equitable economic expansion that tackles inequality, empowers diverse segments of society, and fosters sustainable development [7] [14] [15] [20] [21] [24]. This necessitates addressing crucial dimensions like inclusion, GDP growth, and sustainability, in addition, more specific issues must be taken into consideration like educational improvement and healthcare access, inclusive economic policies, robust social protection, and dismantling systemic barriers such as discrimination and gender inequality [28].

The pursuit of inclusive growth, specifically its dimensions and issues, demands governments to wield the critical responsibility of identifying effective tools and frameworks, prioritizing broad-based participation in economic progress [25] [30]. In this endeavor, government policies serve as the cornerstone, not only for local inclusivity but also for Solidifying a nation's position among leading global actors.

Policymakers and economists grapple with the challenge of shaping economic structures, often through fiscal and monetary tools, to foster inclusive outcomes. Among these, public spending emerges as a key instrument capable of influencing various dimensions of inclusive growth. There are different synonyms that are used globally to express public spending as public expenditure, government spending and/or government expenditure [22]. These terms have been mentioned so that they can be used interchangeably in further explanations.

Public expenditures have two main functions: producing non-market services (education, health care, military, policing, and so on) and redistribution of income (social benefits, subsidies, security and safety transfers) [4]. The general government collects taxes and social contributions to cover the costs of these services. A portion of these funds is used to pay the wages of public personnel, as well as the intermediate consumption and investment required to produce non-market services that are provided for free. The remainder is allocated as social benefits or subsidies [17].

2. Methodology:

The paper investigates the nexus between public spending and inclusive growth for nine developing economies within a period from 1990 to 2020. The methodology consists of 2 approaches, the first is utilizing principal component analysis approach (PCA) to adopt an inclusive growth variable from different proxies [5]. The second is using the generalized method of moment approach (GMM) to estimate the effectiveness of public spending on inclusive growth [2] [6] [8] [10].

2.1 Model Specification:

The model used in estimating the effect of government spending on inclusive growth is based on the study of Samina Sabir [22], the model is specified in the following equation:

$$IGit = \beta 0 + \beta\ 1\ GEEit + \beta 2\ GEHit + \beta 3\ GCEit + \beta 4\ MEX + \beta 5\ UNEMit + \varepsilon it \text{ ………(1)}$$

Where:

IGit = dependent variable that is an index of inclusive growth comprising from the indices

GEEit = gov. expenditure on education.

GEHit = gov. expenditure on healthcare.

GCEit = gov. final consumption expenditure.

MEXit = gov. military and defense expenditure.

UNEMit = unemployment rate.

εit = the error term

i = countries, and, t= 1990, …, 2020.

2.2 Data Sources:

The study uses panel data of 9 developing economies (Argentina – Belarus – Brazil – China – Colombia – Ecuador - Egypt – India - Indonesia) over the period from 1990 to 2020. The main variables for investigating the impact of government expenditure on inclusive growth are government final consumption expenditure, government expenditure on education, government expenditure on health, and government military expenditure. In addition, unemployment rate. While inclusive growth variable was calculated by principal component analysis (PCA) using school enrolment, life expectancy ratio, gross domestic product per capita, Gini coefficient, age dependency ratio, employment to population ratio, access to electricity percentage, adjusted net savings and carbon dioxide emissions variables. All the data was obtained from world development indicators data base the World Bank [32][33] and at: https://databank.worldbank.org.

2.3 Construction of the Dependent variable:

The dependent variable is inclusive growth which is a qualitative term that has no value but could be deducted from several indicators. Although, World Economic Forum (WEF) developed an index for inclusive growth using the same indicators that the study uses, these indicators were in 2017 and were used to rank countries according to their achievement of each indicator on a scale from 0 to 10 [34]. Therefore, the study uses Principal component analysis (PCA) on some indices that were unanimously agreed as indicators of inclusive growth to construct inclusive growth quantitative variable not just ranking. The study uses school enrolment, life expectancy ratio, gross domestic product per capita, Gini coefficient, age dependency ratio, employment to population ratio, access to electricity percentage, adjusted net savings and carbon dioxide emissions as indices for inclusive growth.

2.3.1 PCA analysis:

Inclusive growth is a qualitative phenomenon that has no absolute value but could be deducted from several indicators. The study uses Principal component analysis on some indices that were unanimously agreed as indicators of inclusive growth. due to that, the study uses school enrolment, life expectancy ratio, gross domestic product per capita, Gini coefficient, age dependency ratio, employment to population ratio, access to electricity percentage, adjusted net savings and carbon dioxide emissions as proxies for inclusive growth.

PCA serves as a dimensionality reduction technique in high-dimensional datasets with redundant or correlated variables. This statistical method aims to identify a set of uncorrelated axes, known as principal components, that capture the majority of the data's variance, thereby facilitating subsequent analysis while minimizing information loss. [5][12]. The outcome of

(PCA) is new set of variables called PCs that are uncorrelated and ordered. The principal components are ordered such that the first explains the largest proportion of the data's variance, followed by the second, which accounts for the next largest portion, and so on, cumulatively explaining an increasing percentage of the total variance with each additional component [12].

$$IG = \alpha 1\ SC + \alpha 2\ LE + \alpha 3\ GDPC + \alpha 4\ GINI + \alpha 5\ AD + \alpha 6\ ETP + \alpha 7\ AE + \alpha 8\ CO2E + \alpha 9\ ANS + \varepsilon$$

……………………………….. (1)

Where,

IG = inclusive growth, SC = school enrollment in secondary schools, LE = life expectancy ratio, GDPC = gross domestic product per capita, GINI = Gini coefficient, AD = age dependency ratio, ETP = employment to population ratio, AE = access to electricity percentage, CO2E = carbon dioxide emissions, ANS = adjusted net savings.

2.3.2 Empirical results:

Leveraging the properties of eigenvalues and eigenvectors, PCA facilitates the reduction of data dimensionality [5]. This method entails establishing a set of uncorrelated directions, known as principal components, that prioritize the progressive capture of maximal variance within the data. Interestingly, the number of principal components mirrors the dimensionality of the original dataset.

2.3.3 Eigenvalue (EV):

PCA utilizes eigenvalues to gauge the relative explanatory power of each principal component. The first component exhibits the highest eigenvalue, reflecting its capture of the largest cumulative variance proportion. Subsequent components possess successively smaller eigenvalues, signifying their progressively diminishing contributions to the explained variance. This relationship culminates in the final component holding the smallest eigenvalue, representing its minimal explanatory significance [12]. PCA guidelines often suggest prioritizing components with eigenvalues above 1, as they collectively explain at least half of the data's variance. Table 2.1 presents the eigenvalues for Equation 1 within the context of inclusive growth principal component extraction.

Table (2.1) Eigenvalues and % variance of each PC

Number	Eigenvalues	Difference	% Of variance	Cumulative Proportion
PC1	3.15449	0.991139	0.3505	0.3505
PC2	2.163351	0.717127	0.2404	0.5909
PC3	1.446224	0.681139	0.1607	0.7516
PC4	0.765085	0.177547		
PC5	0.587538	0.238857		
PC6	0.348681	0.101284		
PC7	0.247397	0.090251		
PC8	0.157146	0.027057		
PC9	0.130088	---		

It can be notice from table (4.1) that the first PC (PC1) has the largest variation with 35.05%; the cumulative variance of the 1st 3 components (PC1 +PC2 + PC3) is 75.16%. while the EV of the 1st 3 components are greater than 1. Then the first 3 components will be used to adopt inclusive growth variable.

2.3.3.1 Eigenvector (EVEC):

Within the framework of PCA, a data matrix is constructed where each row corresponds to a data point and each column represents a feature. The central objective of PCA lies in identifying a new set of features, termed principal components, that maximize the captured data variance. This is achieved through the computation of eigenvectors (EVEC) of the data's covariance matrix. Notably, the EVEC signify the directions of maximum variance, while the associated EV quantify the corresponding variance magnitudes [12].

PCA sequentially extracts eigenvectors (EVECs), starting with the direction of maximal variance in the data, followed by subsequent directions capturing progressively diminishing variance. These EVECs then serve as the basis for constructing a new set of features, known as principal components (PCs). Each PC represents a linear combination of the original features, with the loadings quantified by the corresponding eigenvector. These loadings are typically presented in an eigenvector loading matrix [5]. Table 2.2 shows the eigenvector that reflects the principal component (PC) of each variable that were extracted from PCA.

Table (2.2) Eigenvector loading

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
AE	0.352	-0.114	0.344	0.091	0.805	-0.181
AD	-0.399	0.279	-0.090	-0.160	0.099	-0.413
ANS	-0.399	0.156	0.029	0.010	0.232	0.517
CO2E	-0.247	-0.551	-0.236	0.286	0.204	0.439
ETP	-0.246	-0.409	0.394	0.538	-0.290	-0.386
GDPC	0.427	-0.050	0.066	-0.005	-0.384	0.253
GINI	-0.005	0.623	0.322	0.579	-0.025	0.241
LE	0.448	-0.068	0.084	-0.003	-0.070	0.138
SC	0.231	0.137	-0.739	0.509	0.098	-0.217

Inclusive growth equation is constructed from the 1st 3 components as follows:

$$PC1 = 0.369\,SC + 0.518\,LE + 0.421\,GDPC + 0.311\,GINI + 0.326\,AD + 0.143\,ETP + 0.417\,AE - 0.133\,CO2E + 0.047\,ANS \quad \ldots\ldots\ldots\ldots (2)$$

$$PC2 = 0.129\,SC - 0.065\,LE - 0.210\,GDPC - 0.359\,GINI + 0.476\,AD + 0.349\,ETP + 0.092\,AE - 0.562\,CO2E + 0.366\,ANS \quad \ldots\ldots\ldots\ldots (3)$$

$$PC3 = -0.445\,SC + 0.098\,LE + 0.209\,GDPC + 0.339\,GINI - 0.078\,AD + 0.520\,ETP - 0.384\,AE - 0.079\,CO2E + 0.451\,ANS \quad \ldots\ldots\ldots\ldots (4)$$

The researcher reaches to the final inclusive growth equation by adding the 3 components as shown in equation (5):

$$IG = 0.054\,SC + 0.551\,LE + 0.421\,GDPC + 0.291\,GINI + 0.724\,AD + 1.012\,ETP + 0.124\,AE + 0.350\,CO2E + 0.864\,ANS \quad \ldots\ldots\ldots\ldots (5)$$

Inclusive growth can be calculated by substituting with the actual data regarding each variable in equation (5). All the variables have positive impact on inclusive growth. From equation (5) it was concluded that employment to population ratio has a coefficient of 1.012 which means that it is the most significant variable in deriving inclusive growth. Contrastly, adjusted net savings was the second important variable in extracting inclusive growth with a coefficient of 0.864. school enrollment was the least significant variable in extracting inclusive growth with a coefficient of 0.054.

2.4 Investigating the nexus of public spending and inclusive growth:

Generalized Method of Moments (GMM) model is used for the variables gov. final consumption expenditure, gov. expenditure on education, gov. expenditure on health, and gov. military expenditure, in addition to unemployment rate to investigate the effectiveness of public spending on inclusive growth in Argentina – Belarus – Brazil – China – Colombia – Ecuador - Egypt – India - Indonesia over the period from 1990 to 2020.

GMM emerges as a statistical approach for estimating unknown parameters in economic models. This method leverages observed economic data alongside information embedded within population moment conditions to yield parameter estimates [37]. Essentially, GMM operates as a form of instrumental variable (IV) regression, akin to the two-stage least squares (2SLS) technique [38]. Notably, GMM offers the advantage of not requiring complete knowledge of the underlying data distribution [10].

2.4.1 Model equation:

The Variables used in estimating the impact of government expenditure on inclusive growth could be shown in the following equation:

$$IGit = \beta 0 + \beta\ 1\ GEEit + \beta 2\ GEHit + \beta 3\ GCEit + \beta 4\ MEX + \beta 5\ UNEMit + \varepsilon it \ \ldots\ldots\ldots\ldots.. (6)$$

Where i represent countries, t is time period, t= 1990, …, 2020.

While, IGit is the dependent variable that is an index of inclusive growth comprising from the indices previously mentioned in equation (5).

This research posits that government expenditure on education (GEE) directly influences inclusive growth. The hypothesis proposes that GEE enhances labor skills, subsequently leading to increased productivity and greater participation of marginalized groups within society.

GEH is gov. expenditure on healthcare. It is expected that increasing gov. expenditure on health to has direct relation with inclusive growth. It is expected that gov. health expenditure enhances population health which will increase labor productivity on the long run also giving equal opportunities in getting suitable treatment and healthcare that increase equality and reduce poverty.

GCE is gov. final consumption expenditure, it reflects 2 categories of expenditure. First, expenditure for collective consumption for instance national security, justice and providing public services like electricity and sanitation. This category is often known as public goods and services. The second category is expenditure reflect expenditures incurred by government on behalf of individual household like social transfers, individual social security programs, housing. it is expected that GCE has positive impact on inclusive growth.

MEX is government military and defense expenditure. MEX is expected to have two opposite effects on inclusive growth. First it is expected to have negative effect on inclusive growth as increasing expenditure on defense will decrease the proportion of other government expenditures that helps in achieving inclusive growth.

While secondly, increasing military expenditure could have positive effect as it increases international stability and secure investments environment. Consequently, the direction of the relation is determined according to the domination of one of the two effects against the other.

UNEM is unemployment rate. it is expected that there is a negative relation between economic growth and unemployment. Respectively, while economic growth is one of the dimensions of inclusive growth, the study expects that increase in unemployment rate decreases inclusive growth.

The logarithmic form of the equation was chosen for several reasons. first, to capture the nonlinear relationship between variables. Second, to make data more interpretable as the parameters of the model will represent elasticities to get the precise effect of government expenditure on inclusive growth. Lastly, to affect the distribution of data to be more normally distributed and reduce the effect of outliers. Equation (7) shows the logarithmic form of equation (6) as follows:

Log IGit = β0 + β 1 Log GEEit + β2 Log GEHit + β3 Log GCEit + β4 Log MEX + β5 Log UNEMit + εit ……………………….………… (7)

2.4.2 Unit root test for panel data analysis:

Before conducting the model, examining stationarity of data is an essential issue to be discussed. Non-stationarity could arise from the founding of a unit root and/or a trend in the data generating process.

Regression analysis conducted on non-stationary data can yield spurious and unreliable results [6, 13, 18]. This concern is particularly relevant for time series data, which often exhibit non-stationarity or trends, and can also apply to panel data. Therefore, testing for stationarity in both time series and panel data is crucial before proceeding with regression analysis. Established methods like the Augmented Dickey-Fuller, Phillips-Perron, Levin-Lin-Chu, Pesaran-Shin W-stat, and Breitung t-stat tests offer valuable tools for assessing stationarity in panel data.

In the realm of empirical research, the availability of panel data has spurred widespread adoption of dedicated unit root testing methodologies. The pioneering work of Levin and Lin (1992, 1993) [13] highlighted the deficiencies of traditional single-series tests like DF, ADF, and PP in reliably distinguishing a unit root null from stationary alternatives, particularly with limited data. Panel data unit root tests address this weakness by leveraging the information embedded in multiple cross-sectional units, thereby enhancing the power of unit root detection and leading to more reliable conclusions regarding the dynamics of the data.

The stationarity tests are performed on the assumption that variables have a unit root. Unit root mean that the variable is non-stationary. Table (2.3) shows the results of unit root test at level using Levin, Lin, Chu T test and Pesaran & shin W-stat test at the intercept and at intercept and trend.

Table (2.3) panel data unit root test results:

variable		Levin, Lin & Chu T		LM, Pesaran and shin W-stat	
level					
		intercept	**intercept & trend**	**intercept**	**intercept & trend**
IG	**statistic**	-1.41744	-1.13690	0.92984	0.79937
	prob	0.0782	0.1278	0.9618	0.7880
GCE	**statistic**	2.72864	-0.37501	4.23178	0.39509
	prob	0.9968	0.3538	1.00	0.6536
GEE	**statistic**	0.71641	-0.51149	2.23837	-2.28432
	prob	0.7631	0.3045	0.9874	0.0112
GEH	**statistic**	2.41023	0.51047	3.12729	1.94865
	prob	0.9920	0.6951	0.9991	0. 9743
UNM	**statistic**	-0.75201	-0.77106	-1.61203	-0.93089
	prob	0.2260	0.2203	0.0535	0.1760

Both the Levin-Lin-Chu and Im-Pesaran-Shin W unit root tests revealed that, at level I(0) with intercept and intercept with trend, virtually all variables exhibited non-stationarity. Notably, inclusive growth (IG) emerged as the sole exception in the Levin-Lin-Chu test, displaying stationarity at level for both intercept and GEE, while stationary at level with intercept with trend in the Pesaran-Shin W test. Consequently, the data underwent differencing to facilitate further analysis of unit root presence. Table (2.4) shows the results for the unit root test at first difference as follows:

Table (2.4) panel data unit root test first difference:

variable		Levin, Lin & Chu T		LM, Pesaran and shin W-stat	
First difference					
		intercept	intercept & trend	intercept	intercept & trend
IG	statistic	0.91789	4.24778	-2.10942	0.90321
	prob	0.8207	1	0.0175	0.0816
GEE	statistic	-4.88940	-2.08678	-12.7947	-11.3072
	prob	0	0.0185	0	0
GEH	statistic	-2.85563	-2.20837	-7.64605	-7.32618
	prob	0.0021	0.0136	0	0
GCE	statistic	-3.03761	-0.64727	-5.88269	-4.26018
	prob	0.0012	0.41365	0	0
UNM	statistic	-1.19695	0.02935	-4.83426	-2.90480
	prob	0.1157	0.1157	0	0.0018

While conducting stationarity tests for the economic variables, the analysis yielded mixed results. For government final consumption expenditure, government expenditure on education, and government expenditure on health, the Levin, Lin & Chu test confirmed I(1) stationarity. However, inclusive growth and unemployment exhibited non-stationarity at I(1) with and without trend in the same test. Notably, applying the LM, Pesaran & Shin W-statistics test rendered all variables stationary after differencing them once.

3. Empirical results:

As mentioned in section 2, in estimating the impact of gov. expenditure on inclusive growth using panel data analysis, it is more fitting to use GMM [37]. The following results were shown after performing the analysis on 9 developing economies over the period 1990-2020.

Table 4.3 panel data Generalized method of moment approach (GMM) results:

dependent variable: Inclusive growth log (IG)			
variables	**coefficient**	**t-stat**	**prob**
Log (GEE)	0.440622	3.585448	0.0071
Log (GEH)	0.158054	6.238963	0.0002
Log (GCE)	-0.1770696	-0.880431	0.4043
Log (MEX)	0.211442	8.585631	0.0000
Log (UNEM)	-0.110433	-3.159291	0.0134
J-statistic	6.216797	**Instruments rank**	9
Prob(J-statistic)	0.183532		

Within the context of GMM estimation, the J-statistic serves as a more favored criterion compared to the F-statistic for assessing model validity [26, 37]. The probability associated with the J-statistic provides insights into the model's goodness-of-fit and the instrument's effectiveness in explaining the model's variables. In this study, the observed p-value of the J-statistic exceeding 0.05% suggests that the chosen instrumental variables (IVs) possess adequate explanatory power over the model's variables and are statistically significant in estimating the impact of independent variables on inclusive growth across the analyzed countries and timeframe (1990-2020).

For each independent variable, the results showed that all independent variables are significant except gov. consumption expenditure (GCE) which was insignificant.

The probability of gov. expenditure on education (GEE) showed a significant level of 1% as its p-value scored 0.0071. with a coefficient of 0.4406, due to logarithmic form of equation, a 1% change in gov. expenditure on education changes inclusive growth with 0.44%. the results came like expected that increasing gov. expenditure on education by 1% will increase inclusive growth by 0.44% as mentioned that building capacities and human capital investment through education enhances individual skills leading to increase in production.

Like gov. expenditure on education (GEE), the p-value of gov. expenditure on healthcare (GEH) showed a significant level of 1% as its probability was 0.0002. with a coefficient of 0.158, the results revealed a direct relation as expected between gov. expenditure on healthcare and inclusive growth. For each 1% increase in (GEH) inclusive growth increases by 0.158%.

Also, gov. military expenditure (MEX) was significant at 1% with p-value 0.000. Its' coefficient scored 0.221. for military expenditure the positive effect dominates the negative one as the results clarified that for each 1% change in gov. military expenditure (MEX), inclusive growth increases by 0.22%.

Furthermore, unemployment rate (UNEM) showed significance with p-value < 0.05 with a negative sign as expected and a coefficient score of -0.110. which means that at each 1% increase in unemployment rate, inclusive growth decreases by 0.11%.

Unlike what expected, government final consumption expenditure (GCE) was insignificant in affecting inclusive growth. The reason could be due to the inefficiency in allocating expenditures, also strongly suggested that a considerable part of government expenditures took the form of cash transfers, grants and exhaustive goods which has a short-term effect not sustained over time.

4. Conclusion:

Based on the preceding analysis, the paper contends that the economic and social environment for inclusive growth takes precedence in determining which types of expenditure deserve policymakers' attention. This is because different expenditure categories exhibit varying elasticities and impacts on inclusive growth. Notably, government expenditure on education emerges as the most dominant variable, accounting for over 44% of the influence on inclusive growth. Government expenditure on healthcare and military expenditure also contribute, with respective shares of 15% and 21%. Furthermore, the research recommends greater policy focus on the unemployment rate due to its negative impact on inclusive growth (scored at 11%).

The authors further assert that government expenditure itself stands as a key determinant of inclusive growth. This observation finds support in the diverse impacts of government expenditures across the various dimensions of inclusive growth. In the economic growth dimension, government expenditures are well-known to positively influence productivity and manage unemployment. Within the inclusion dimension, they play a crucial role in income redistribution and poverty reduction. Finally, government expenditures also hold significant sway in the sustainability dimension, impacting adjusted net savings for future generations and shaping incentives for environmentally-friendly and carbon-conscious investments, while contributing to international stability through military expenditure.

- **Conflict of Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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