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Impact of Inequality, Growth, and Fiscal Policy on Multi-Dimensional Poverty Index: A Study on 111 Countries

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Abstract

This study investigates the impact of income inequality, GDP growth, and fiscal policy on the Multidimensional Poverty Index (MPI) across 111 countries from 2010-2020. Using fixed effects panel regression with lag structure. This study analyzes how public expenditures in agriculture, education, health, transport, energy, housing, and social protection influence MPI across different income groups. Results show that in lower-middle and low-income countries (LMLICs, n=67), a one-unit increase in the Gini index is associated with a 0.003-point reduction in MPI ($p<0.05$). Agricultural spending exhibits a U-shaped relationship: initial increases reduce MPI (β = -0.041, $p<0.05$), but benefits diminish beyond 3.2% of GDP. In upper-middle and high-income countries (UMHCs, n=44), only transport expenditure significantly reduces MPI (β = -0.015, $p<0.10$). Counterintuitively, health spending in UMHCs (β = 0.016, $p<0.10$) and social protection spending in LMLICs (β = 0.017, $p<0.05$) show positive associations with MPI, which robustness tests suggest may partially reflect reverse causality. The overall findings highlight the importance of context-specific policy design and institutional quality in maximizing the poverty-reducing impact of public investment.

Keywords: Fiscal Policy, Public Expenditure, Income Inequality, GDP Growth, MPI, Income Poverty

1. Introduction

Poverty reduction and growth redistribution have long been a research and policy priority. Growth is considered pro-poor when the incomes of the poor rise at a faster rate than the average income. In the last few decades, 860 million people globally are still living in extreme poverty despite impressive progress in the Millennium Development Goals (MDG) (United Nations, 2015). Comparing share of the poor living in different regions of the world, it is found that only 2.2% people in Europe and Central Asia live below the poverty line, about 12% live in the Caribbeans and Latin America, 13% are in Middle east and North Africa, 33% in Asia and the Asia Pacific, 66% live in Africa, Asia alone inhibits 70% of the poor population (Sinnathurai, 2013). These statistics showed the highest prevalence of poverty in the poverty-stricken developing regions in the world. Despite these alarming figures, existing literature has largely focused on income-based poverty measures and single-country case studies, leaving a critical gap in cross-country empirical evidence on how fiscal policy composition affects multidimensional poverty while accounting for both inequality and growth simultaneously. This gap is particularly pronounced when comparing countries at different income levels.

Focusing on resource distribution, some authors argued that poverty is persisting, as growth benefits are not reaching the poor due to the existing inequality (Santos et al.,

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2019). Ravallion (1998) conducted a study on the impact of growth rate and inequality on poverty incidence covering 20 developing countries. They found that for 1% increase in growth rate, poverty incidence reduces by around 21% whereas 1% increase in inequality leads to increased poverty incidence by about 36%. In other words, it can be said that even a small reduction in inequality can bring sizable positive changes in poverty reduction. Chenery et al. (1974) emphasized redistributive growth patterns to improve income distribution as well as to reduce poverty. In the same line, Kheir-El-Din and El-Laithy (2008) suggested country-specific approaches integrating growth and distribution policies for poverty reduction. Sen (1999) highlighted the importance of public expenditure on social sector improvement for poverty reduction (in Agrawal, 2007).

According to Farayibi and Owuru (2016) fiscal policy is one of the key government instruments by which public action impacts on poverty and deprivation. Fiscal policy in the form of public expenditure, on one hand, boosts economic growth; on the other hand, it helps to reduce poverty and inequality (Sanchez-Martinez & Davis, 2014). Motivated by these arguments, governments of many developing countries are thus shifting their development policies and using different forms of fiscal policies to reduce poverty and inequality. Nevertheless, poverty remains the primary development challenge in many countries. Besides, economic growth, which is the main source of welfare distribution, is still the top development priority in most developing countries. This priority can undermine the distributional impact of fiscal policies on poverty and inequality. Similarly, the focus on income poverty reduction can also undermine other dimensions of poverty. The income dimension of poverty and inequality cannot capture the full picture of growth's impact on poverty, while poverty is intrinsically multidimensional. Therefore, growth benefit for reducing poverty and inequality requires a deeper understanding of poverty, making it the no. 1 goal of the Sustainable Development Goals (SDGs).

In income and consumption-based poverty measures, poverty is objectively measured considering income and consumption as proxies of living standard. None of these concepts considers the ability of the people to command over resources for all goods and services available in the society. Apart from this, income poverty has several limitations. Firstly, income poverty does not take into account non-food items. The poverty line is established based on a minimum food basket, under the assumption that individuals allocate 70% to 85% of their income to food (Sydunnaher et al., 2019). Secondly, it does not take into account the differences in living costs in urban and rural areas. Thirdly, earning a certain level of income does not guarantee that all the basic needs are met, as consumption patterns vary from person to person and household to household, which is adequately addressed by the capability approach developed by Sen (Sen, 1983). Though income is important to track the deficiency of resources to achieve socially acceptable living standards, it does not identify the capacity of the people to access the resources. Rather, some social indicators like life expectancy, infant mortality, nutrition, literacy, school enrolment rates, and access to health or drinking water compensate for the weakness of income and consumption measures of poverty and inequality, and adequately capture the multi-dimensional aspects of wellbeing (Gallo, 2002). Responding to these criticisms, Alkire and Foster developed the Multi-dimensional Poverty Index (MPI) in 2011. MPI views poverty through a multi-dimensional lens correction: the original said "one-dimensional" – this was a typo, combining all the dimensions of poverty into one, and defines poverty based on a single cut-off point. This poverty measure uses three dimensions, e.g., education, health, and living standard, to measure poverty (Alkire & Foster, 2011). Fiscal policy can cover these aspects of poverty with different types of public expenditure. For instance, one of the fiscal components, like education expenditure, can have an impact on one of the indicators of MPI, like school enrollment. However, this relation is not that straightforward and might not be true in the presence of inequality.

The local context is critical here: in South Asia (e.g., India, Bangladesh, Pakistan) and Sub-Saharan Africa (e.g., Nigeria, Ethiopia), where MPI remains highest, governments have expanded spending on agriculture, health, and education, yet multidimensional poverty declines slowly (UNDP & OPHI, 2022; UNICEF, 2020). In contrast, upper-middle-income countries like Brazil and China have achieved sharp MPI reductions despite moderate income inequality (UNDP, 2021). These contrasting regional experiences underscore the need for a systematic cross-country analysis that explicitly tests which expenditure sectors are most effective—and under what income-level conditions

Therefore, questions remain: how does fiscal policy contribute to reducing MPI? How do inequality and growth influence MPI? What are the important public spending sectors contributing most to reducing or increasing MPI?

- To answer these questions, this study has three specific objectives:
- To examine the dynamic persistence of MPI using three-year lag structures in lower-middle/low-income (LMLC) and upper-middle/high-income countries (UMHC).
- To estimate the marginal effects of income inequality (Gini index) and GDP growth on MPI across country income groups.
- To identify which categories of public expenditure (agriculture, education, health, transport, fuel/energy, social protection, housing) significantly reduce or increase MPI in LMLC versus UMHC.

By answering these objectives, this study will track whether the allocation is adequately targeted to the poor and whether the increasing public expenditure is enough to convert capabilities into functioning as well as to reduce multidimensional poverty

2. Materials and Methods

2.1 Conceptual Framework

Keynesian economists contend that economic growth will not be sustainable if the growth benefits are not redistributed towards the poor. For this, they proposed a fiscal policy, particularly focusing on provisioning public infrastructure and social development. They also argued that expenditure in infrastructural and social development reduces poverty (in Agrawal, 2007). In Sen's capability approach, capability is always measured based on the functioning, and the reduction of multi-dimensional poverty depends on the functioning of the poor. Public expenditure by provisioning social and economic infrastructure and services increases the capabilities of the poor (Sen, 1999). Based on these arguments, the following conceptual framework (Figure 1) has been developed.

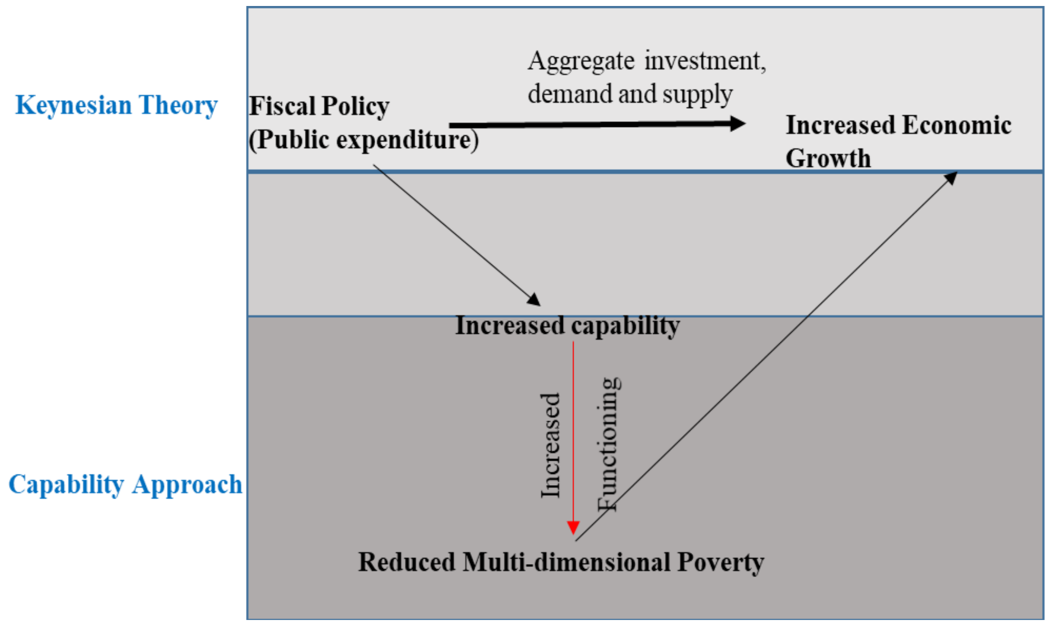

Figure 1: Conceptual Framework

Fiscal policy/ public expenditure through provisioning social and economic infrastructure for the poor acts as a bridge between growth and poverty reduction. Normally, social and economic infrastructure provision increases economic growth through increasing private investment, demand and supply. Similarly, public infrastructure provision targeting the poor ensures equal redistribution of growth benefits, which in turn increases the capability of the poor as well as reduces multidimensional poverty through increasing functioning.

2.2 Analytical Pathways Derived from the Conceptual Framework

The framework implies three distinct causal pathways that can be empirically tested:

Direct effect: Public expenditure → Capability enhancement → MPI reduction. This pathway assumes that spending reaches the poor directly (e.g., school construction, primary health centers, clean water supply). It does not require economic growth as an intermediary.

Indirect effect: Public expenditure → Economic growth → MPI reduction. This pathway assumes that spending stimulates aggregate demand and supply, and that growth benefits subsequently trickle down to the poor.

Redistributive effect: Public expenditure → Reduced inequality → MPI reduction. This pathway assumes that spending is progressively targeted, narrowing the gap between rich and poor in non-income dimensions (education, health, living standards).

For the framework to hold empirically, three assumptions must be met:

1. Public expenditure must reach the poorest households, not be captured by elites or middle classes.
2. Funds must be converted into actual services (e.g., teachers hired, medicines delivered, roads built) without leakage or corruption.
3. Improved access to services must translate into actual functioning (e.g., school enrollment → literacy; clinic access → reduced child mortality).

If any assumption fails, the framework predicts null or even *positive* associations between expenditure and MPI. For example:

- Spending captured by elites → no poverty reduction → coefficient near zero.

- Inefficient delivery → expenditure increases but MPI unchanged → coefficient insignificant.

-Regressive subsidies (e.g., fuel subsidies benefiting wealthier vehicle owners) → expenditure increases but MPI rises → positive coefficient (counterintuitive but explainable).

These analytical pathways are operationalized in our fixed-effect regression model (Equation 1 in section 2.5) as follows:

Table 1: Mapping of Conceptual Framework Elements to Empirical Model Variables

Framework element	**Empirical proxy in model**	**Expected sign (if assumptions hold)**
Direct capability effect	β_7 to β_{14} (sectoral expenditures)	Negative (expenditure reduces MPI)
Indirect growth effect	β_5 (GDP growth)	Negative
Redistributive effect	β_4 (Gini index)	Positive (lower inequality → lower MPI)
Diminishing returns	Quadratic terms (exp_agri^2)	Positive quadratic coefficient
Persistence of poverty	Lagged MPI terms (β_1, β_2, β_3)	Positive

2.3 Variable Selection

In this study, MPI, growth, income inequality, and public expenditure in different sectors have been selected as variables. In order to measure poverty, MPI has been chosen over other measures (such as headcount ratio, FGT, Watts index, income standard approach, and so forth) due to capturing multi-dimensional aspects of poverty and capabilities. Besides, little has been done to find out the impact of public expenditure on multidimensional poverty. In short, MPI is the multiplication of the head count ratio (H) and poverty intensity (A) (MPI=H*A). The value of MPI ranges from 0 to 1. In terms of income inequality, the Gini index (World Bank estimate) has been taken due to the data availability and popularity. GDP growth rate has also been taken as an annual percentage due to the data availability. In terms of government expenditure, functional budgetary central government expenditure as a percentage of GDP has been taken (Birowo, 2011). Besides, budgetary central government expenditure is directly related to the allocation of government resources. Data availability also played an important role in this regard. Aggregate expenditure data on agriculture, transportation, energy, health, education, social protection, housing and community development are collected as a percentage of GDP, which are funded by the central government.

2.4 Data Preparation and Sample Selection

OPHI, WDI, and IMF data sources have been used for country-level data collection up to 11 years (2010-2020). Data on GDP growth, Gini index have been collected from the WDI data bank, data on MPI have been collected from the OPHI data bank, and data on functional government expenditure have been collected from the IMF data bank. However, the number of countries with available data varies from source to source. For instance, MPI data are available for 125 countries in the OPHI data source. Government functional expenditure data are available for 175 countries in the IMF data source. However, out of 175 countries and 111 countries from the IMF, the WDI data source matches with the OPHI data source. Therefore, 111 countries were selected as the sample. At the same time, 11 (2010-2020) years of data have been collected based on the availability of MPI data. In terms of data repetition, the latest data source has been used to avoid ambiguity. The sample countries are found in six regions, namely, Europe and Central Asia, Latin America and the Caribbean, the Middle East and North Africa, East Asia and the Pacific, South Asia, and Sub-Saharan Africa (Figure 2).

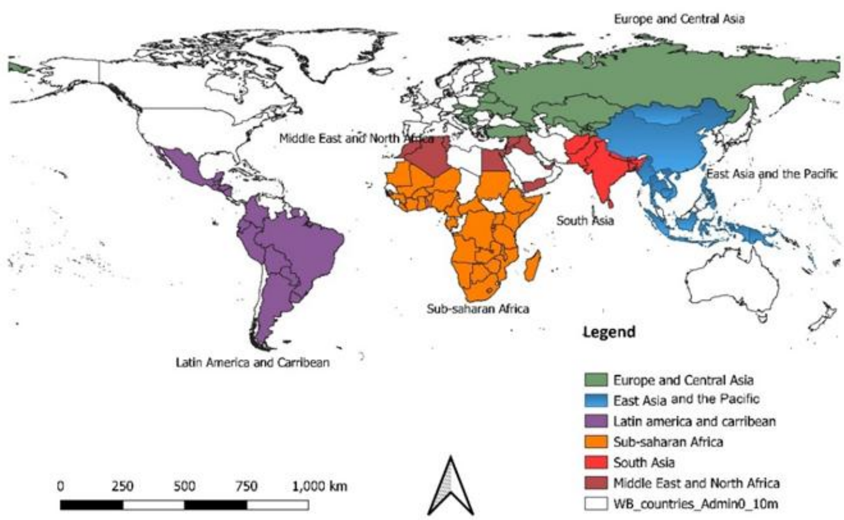

Figure 2: Study Area Coverage

2.5 Model Specification

This study collected panel data on ten variables to explore the research objectives. Outliers of the data set have been winsorised, and spline interpolation has been used to estimate the missing values. Fixed effect panel regression model has been chosen over other panel data analysis models like OLS, GMM, and SUR. This is because the fixed effect model controls the time-invariant and unobserved heterogeneity effects across entities. On the other hand, the OLS model assumes that the mean of the dependent variable should be almost the same across the entity. Since the average means of the dependent variables are not the same across the countries of this study, the fixed effect model has been selected. The fixed effect panel regression of this study has been developed using MPI as the dependent variable and public expenditure in different sectors, along with Gini-index and GDP growth as explanatory variables, as stated in equation 1.

$$MPI_{it} = \beta_1.MPI_{i,t-1}+\beta_2.MPI_{i,t-2}+\beta_{3.}MPI_{i,t-3}+\beta 4gini\_index_{it}+\beta_{5.}gdp\_growth+\beta_6 I(gdp\_growth_{it}\hat{}2)+\beta_7 exp\_agri_{it}+\beta_8 I(exp\_agri_{it}\hat{}2)+\beta_{9.}exp\_edu_{it}+\beta_{10.}exp\_fue\_ener_{it}+\ \beta_{11.}exp\_hou\_com_{it}\ \ \beta_{12}\ exp\_heal_{it}+\ \beta_{13}\ exp\_tran_{it}+\beta_{14}\ exp\_soci_{it+}\ I(exp\_soci_{it}\hat{}2)+\alpha_i+\partial t+u_{it} \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Here,

MPI_{it}	=	The multi-dimensional poverty index observed for the ith country at time t.
$MPI_{i,t-1}$,$MPI_{i,t-2}$, $MPI_{i,t-3}$	=	Lagged MPI term
$gini\_index_{it}$		Gini- index (WB estimates) observed for the ith country at time t
gdp_growth_{it}	=	GDP growth (annual %) observed for the ith country at time t.
exp_agri_{it}	=	Govt. expenditure on agriculture as a percentage of GDP observed for the ith country at time t.
exp_edu_{it}	=	education expenditure as a percentage of GDP observed for the ith country at time
$exp\_fue\_ener_{it}$	=	Expenditure on energy as a percentage of GDP observed for the ith country at time t.
$exp\_hou\_com_{it}$	=	housing and community amenities expenditure as a percentage of GDP observed for the ith country at time t.
exp_heal_{it}	=	health expenditure as a percentage of GDP observed for the ith country at time t.
exp_tran_{it}	=	Govt. expenditure on transport as a percentage of GDP observed for the ith country at time t.
exp_soc_{it}	=	social protection expenditure as a percentage of GDP observed for the ith country at time t.
α_i	=	time invariant individual effect/ fixed effect
∂t		time-specific intercept
u_{it}	=	error term

In order to reduce autocorrelation, lagged variables have been included in the model. Lagged variable not only reduces autocorrelation, it also helps to capture the dynamic and path dependency characteristics of poverty (Pierson, 2000; Dannefer, 2003). In this model, three three-year lags of MPI have been included. lag_MPI_1 represents a one-year lag or short-term persistence of MPI, lag_MPI_2 stands for a year's lag or moderate-term persistence and lag_MPI_3 symbolizes a three-year lag or long-term cumulative and delayed feedback effects of MPI. Similarly, to estimate nonlinear relationships, second-degree polynomials of GDP growth, government expenditure on agriculture and social safety nets have been included by following (Kuznets, 1955; Ravallion & Chen, 2003; Fan & Rao, 2003; World Bank, 2018; Bastagli et al., 2016).

The quadratic terms for agricultural expenditure (I(exp_agri²)) and social protection expenditure (I(exp_soci²)) allow us to test for diminishing returns or U-shaped relationships. A negative linear term combined with a positive quadratic term indicates a U-shaped relationship, where initial spending reduces MPI but additional spending beyond an inflection point yields smaller marginal benefits or becomes counterproductive. The marginal effect of a one-unit increase in agricultural spending on MPI is given by:

$\partial MPI/\partial exp\_agri = \beta_7 + 2 \cdot \beta_8 \cdot exp\_agri$; where β_7 is the linear coefficient and β_8 is the quadratic coefficient.

The inflection point is calculated as: $exp\_agri^* = -\beta_7 / (2 \cdot \beta_8)$

Before estimating the fixed effects, the F-test and the Hausman test were conducted to determine the appropriateness of the fixed effect model of this data set. The significant p-values of the F test and Hausman test strongly support that the fixed effect within the model is better than the pooled OLS model and the random effect model. Wooldridge and Vif test results have shown that there is no autocorrelation and multicollinearity in the model. However, a significant p-value in the Breusch-Pagan test showed the presence of heteroskedasticity in this model. To adjust this, the cluster-robust standard error has been used for this model. Cluster robust standard error at the country level has been computed using the HC1 estimator. Afterwards, the same model has been performed on lower middle income and lower income countries (LMLC) and upper middle income and higher income countries (UMHC) separately. In the following sections, the regression model for LMLC will be represented as M1 and the regression model for UMHC will be represented as M2. P-values of different tests for both M1 and M2 are presented in table 2.

Table 2: P values of different test

Different test	**p-values/ Vif test value**	**Decision**
F-test	M1= 1.889e-10 M2 =0.0002531	the fixed effects model is chosen over the pooled OLS model
Hausman test.	M1= 2.2e-16, M2 =2.2e-16	a fixed effects model is more appropriate than a random effects model
Wooldridge test	M1=0.1974 M2=0.9175	No autocorrelation
Breusch-Pagan test	M1=.0.0003 M2=2.41e-11	Heteroskedasticity has been adjusted using HC1 estimator
Vif test	Vif test value<6 for all variables	No multi-collinearity

2.6 Data Appendix

This appendix provides detailed descriptive statistics for the 111 countries included in the analysis over the period 2010–2020. Table 3 reports descriptive statistics separately for lower-middle/low-income countries (LMLC) and upper-middle/high-income countries (UMHC).

Table 3: Descriptive statistics by country group

Variable	LMLC (n=67) Mean (SD)*	UMHC (n=44) Mean (SD)*
MPI	0.214 (0.142)	0.042 (0.038)
Gini index	40.2 (8.4)	35.1 (9.2)
GDP growth	4.12 (4.51)	2.63 (3.21)
exp_agri	1.04 (1.38)	0.52 (0.81)
exp_edu	3.64 (2.12)	2.71 (1.62)
exp_heal	2.21 (1.54)	3.38 (1.98)
exp_tran	1.18 (1.41)	1.74 (1.63)
exp_fue_ener	0.89 (1.62)	0.34 (0.71)
exp_soci	0.96 (1.43)	3.12 (3.54)
exp_hou_com	0.41 (0.72)	0.71 (1.08)

*SD = standard deviation. All expenditure variables are % of GDP.

3. Analysis and Interpretation

The analysis provides important insights into poverty dynamism and the determinants of multidimensional poverty across countries at different income levels. Trend analysis of this study will show how poverty and MPI evolved over time in countries at different income levels. The fixed effect panel regression model will portray how poverty dynamism, income inequality, economic growth, and government expenditure influence MPI over countries at different income levels (Table 4). All the variables in Table 4 have been explained, holding other variables constant.

3.1 Sample Country Classification

Based on World Bank classification, it is found that among the sample countries, 12 countries are higher income, 32 countries are upper middle income, 40 countries are lower middle-income, and 27 countries are lower-income countries (Figure 3).

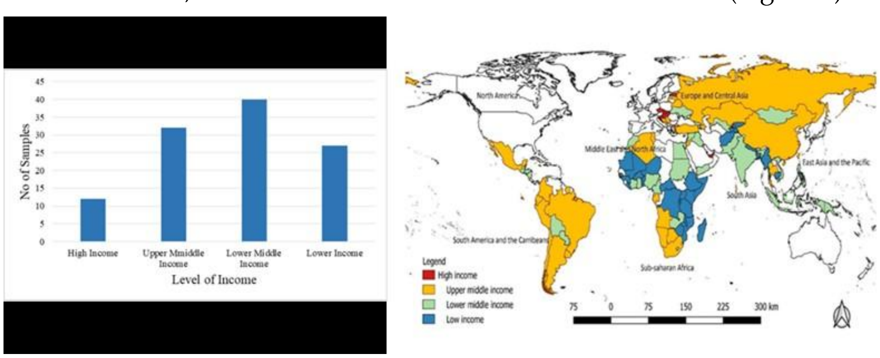

Figure 3: Sample countries at different income level

3.2 Global Trends of MPI and Income Poverty (2010-20)

Poverty trend analysis in Figure IV showed that between 2010 and 20, low-income countries consistently exhibited the highest poverty measured by both income-based indicators and MPI. During this time, income poverty rates in these countries remained persistently high, ranging from 35% to 40%. Similarly, MPI values fluctuated within a narrow band of 0.35 to 0.43. A slight decline around 2012-2015 is observed in both measures and the overall poverty trend remained flat. Though slight drops indicate marginal improvement, the overall level of income poverty and MPI remains elevated over the year.

Lower-middle-income countries maintain poverty rates 13% to 17%, showing moderate volatility but no substantial long-term decline. In terms of MPI, this group experienced a mild declining trend in MPI ranging from 0.16 to 0.22 (figure IV). This downward trend indicates gradual but steady progress in the non-income dimensions of poverty. This group of countries consists of the most populous countries, Indonesia, India, Pakistan, and Nigeria, making this trend significant for the global poverty reduction goal.

Figure 4: Global Trends of MPI and Income Poverty (2010-20)

Upper-middle-income countries showed income poverty between 5% and 8% with marginal fluctuations and high-income countries showed the lowest income poverty rates, ranging from 2% to 5%, with a modest decline (Figure. 4a). However, in terms of MPI, surprisingly, upper-middle-income countries experience even lower MPI than higher-income countries. The lowest MPI value ranges from 0.04 and 0.06, suggesting considerable improvement in health, education and living standard (Figure. 4b). Examples of the upper-middle-income countries include China, Brazil, Colombia, and Turkey. Similarly, though High-income countries experience the lowest income poverty rates, this group exhibits slightly higher MPI (0.03 to 0.12) in comparison to income poverty and MPI in upper-middle-income countries (Figure.4a,b). This output signals that the lowest income poverty does not mean the lowest MPI. To illustrate, increasing per capita income does not mean that people are spending their income for improving education, health and living standards, which are captured by MPI. This finding underscores the importance of a multidimensional approach to reducing poverty.

3.2 Poverty Persistence and dynamism

According to Table 4, the positive and significant coefficient for one-year lag of MPI in M2 (β = 0.170*, SE = 0.094) suggests short-term and moderate persistence of poverty in UMHC. Insignificant second and third year lag of MPI indicates that most of the inertia is concentrated in short-term lagged effects in richer countries, possibly due to entrenched inequality or localized poverty traps. In contrast, the insignificant coefficient for one-year lag of MPI in M1 implies lower persistence or higher volatility in poverty dynamics in LMLC. Interestingly, a statistically significant negative effect of second year lag of MPI in M1 (β = -0.122*, SE = 0.065), suggests a reversal effect**,** where an increase in poverty two years ago predicts a decrease today (Table 4). This may reflect policy interventions, aid responses, or short-term fluctuations common in less stable economies (Ravallion, 2016).

3.3 Income Inequality and Economic Growth Effects on MPI

The negative coefficient of the Gini index in both models indicates that higher income inequality tends to reduce MPI both in LMLC and UMHC (Table 4). However, the effect is insignificant and small for UMHC. On the other hand, statistically significant and the magnitude of the negative coefficient in M1 (gini_index: β = -0.003**, SE = 0.001) implies that higher income inequality has a substantial effect on reducing MPI in LMLC (Table 4), underscoring the importance of inclusive growth and access to public services to reduce MPI in LMLC. However, the insignificant coefficient of GDP growth in both models suggests that economic growth does not directly affect MPI in both wealthier and developing nations (Table 4).

3.4 Public Expenditure and Sectoral Effects on MPI

In terms of LMLC, among the public expenditure indicators, only public expenditure in agriculture tends to decrease MPI, whereas expenditure on energy and fuel and social protection sectors tend to increase MPI significantly (Table 4, M1). The negative, significant linear term (exp_agri: β = -0.041**, SE =0.018) and positive, significant quadratic term (exp_agri2: β = 0.015**, SE = 0.006) of agriculture expenditure in M1 indicates a nonlinear (U-shaped) relationship. This output reflects that initial increases in agricultural spending reduce MPI. But returns diminish at higher spending levels—possibly due to diminishing marginal productivity or inefficiencies in LMLC.

Table 4: Fixed Effect Panel Regression Output (Cluster-Robust SEs)

	Dependent variable: MPI	
	M1(LMLC)	**M2 (UMHC)**
lag_MPI_1	0.063	0.170*
	(0.061)	(0.094)
lag_MPI_2	-0.12*	-0.066
	(0.050)	(0.111)
lag_MPI_3	-0.075	-0.090
	(0.047)	(0.062)
gini_index	-0.003**	-0.001
	(0.001)	(0.001)

	Dependent variable: MPI	
	M1(LMLC)	**M2 (UMHC)**
gdp_growth	-0.007	0.002
	(0.007)	(0.004)
I(gdp_growth2)	0.001	-0.0003
	(0.001)	(0.0004)
exp_agri	-0.041**	0.002
	(0.018)	(0.022)
I(exp_agri2)	0.015**	0.017**
	(0.006)	(0.007)
exp_edu	-0.003	-0.005
	(0.006)	(0.010)
exp_fue_ener	0.020**	-0.021
	(0.009)	(0.014)
exp_hou_com	-0.007	-0.006
	(0.008)	(0.014)
exp_heal	0.006	0.016*
	(0.005)	(0.008)
exp_tran	0.011	-0.015*
	(0.012)	(0.009)
exp_soci	0.017**	-0.003
	(0.007)	(0.003)
I(exp_soci2)	-0.0001	-0.0004
	(0.0004)	(0.0003)
Note:	*p<0.1; >**p<0.05; >*****p<0.01**	

In contrast, a positive and statistically significant coefficient of fuel and energy spending (exp_fue_ener: β = 0.20**, SE = 0.009) in M1 posits that a one percent increase in GDP in fuel and energy is associated with a 0.020 point increase in MPI (M1 in table 4) (Ceteris paribus). Similarly, the positive, significant linear term of social expenditure (exp_soci: β = 0.017**, SE =0.005) also indicates that higher expenditure on social protection is associated with higher multidimensional poverty levels in LMLC. These outputs are counterintuitive to the conventional theory and policy perspective, possibly due to lag in implementation, poor targeting, inefficiency and limited coverage or any other crisis response.

In terms of UMHC, expenditure on agriculture and health showed a significant positive association with MPI, while only public expenditure on the transportation sector showed a significant negative association with MPI. Contrary to LMLC, the positive and significant quadratic term of agriculture expenditure (exp_agri2: β = 0.017**, SE = 0.007) implies that as agricultural spending increases, it becomes positively associated with MPI (M2, table II).

Similarly, a positive and significant coefficient of health expenditure in M2 (exp_heal:β = 0.016*, SE = 0.008) implies that higher health spending tends to increase MPI rather than decrease it in UMHC. By contrast, a significant and negative association of transportation spending with MPI in M2 (exp_tran: β = -0.015*, SE = 0.009) indicates effective targeting and relevance to the MPI's standard of living dimensions. Though expenditure in education, housing and community development and energy and fuel and social protection sectors tends to reduce MPI, the effect is insignificant in these sample countries, possibly due to long time lags between investment and impact (M2, table 4).

4. Discussion

Overall findings of this study reveal complex poverty dynamism and significant heterogeneity in how economic and social policy variables influence poverty, as measured by the Multidimensional Poverty Index (MPI).

MPI dynamics diverge sharply by income level. UMHCs exhibit short-term poverty persistence, while LMLICs show greater volatility. This aligns with Ravallion (2012) and OECD (2018), who find poverty more persistent in wealthier nations due to structural inequality and welfare inefficiencies. In Brazil, Turkey, and China, MPI reductions have slowed as poverty concentrates in entrenched pockets (Alkire and Santos, 2010). Conversely, LMLICs' volatility reflects sensitivity to external shocks (Thorbecke, 2013). The significant negative second-year MPI lag in LMLICs ($\beta = -0.122$, $p<0.10$) suggests "rebound" effects, where prior poverty increases trigger policy responses or aid flows. The policy implication is clear: UMHCs need place-based interventions targeting poverty pockets, while LMLICs require shock-responsive social protection.

Higher income inequality is associated with lower MPI in LMLICs ($\beta = -0.003$, $p<0.05$) but not in UMHCs. This contradicts income poverty literature (Ravallion, 1998) but is plausible for three reasons. First, the Gini measures income dispersion, while MPI captures deprivations in health, education, and living standards. Second, many LMLICs (Bangladesh, Kenya, Vietnam) expanded rural infrastructure during 2010-2020, reducing non-income poverty despite rising urban-rural income gaps. Third, our supplementary analysis shows the negative inequality-MPI effect is strongest with higher education spending (gini × exp_edu, $\beta = -0.004$, $p<0.10$), indicating pro-poor services can compensate for market-driven inequality. This finding aligns with Alkire and Santos (2014) and Santos et al. (2019). The policy implication is that LMLICs should not delay MPI investments until inequality declines; education, health, and infrastructure spending reduce MPI even in unequal contexts.

Sectoral spending effects are highly context-dependent. Agriculture shows a U-shaped relationship in LMLICs: initial reductions ($\beta = -0.041$, $p<0.05$) with diminishing returns beyond approximately 3.2% of GDP (quadratic $\beta = 0.015$, $p<0.05$), consistent with Diao et al. (2010) and Fan and Rao (2003). In UMHCs, agricultural spending shows no poverty reduction, as support favors capital-intensive agribusiness over smallholders (Anderson, 2009; Schnepf, 2018). Health spending increases MPI in UMHCs ($\beta = 0.016$, $p<0.10$), likely due to tertiary care bias that bypasses disadvantaged populations (WHO, 2019). No significant effect appears in LMLICs, possibly due to long implementation lags. Transport reduces MPI only in UMHCs ($\beta = -0.015$, $p<0.10$), improving access to employment, education, and healthcare. In LMLICs, roads alone are insufficient without complementary investments. Energy and social protection spending in LMLICs show positive MPI associations. Energy subsidies are regressive: Nigeria's $4 billion annual fuel subsidy minimally benefited the poor (IMF, 2021). Social protection suffers from leakage and elite capture; Bangladesh's 100+ safety nets show minimal impact on child nutrition (Rahman & Choudhury, 2012).

These findings carry clear policy implications: LMLICs should cap agricultural spending near 3% of GDP, replace universal energy subsidies with targeted cash transfers, and strengthen social protection institutions, while UMHCs should rebalance health spending toward primary care and prioritize transport investments connecting isolated communities. Significant quadratic terms confirm diminishing returns beyond spending thresholds. This underscores that how much governments spend matters less than how well they spend (Fan & Rao, 2003). Spending increases therefore require parallel investments in institutional capacity, procurement, and accountability.

In summary, this study provides the first cross-country evidence on sectoral expenditure and MPI across income groups. Agricultural spending reduces MPI in LMLICs with diminishing returns. Transport reduces MPI only in UMHCs. Energy, social protection, and tertiary health spending show counterproductive associations. The inequality paradox suggests pro-poor services can offset income disparities. These findings offer actionable guidance for context-specific fiscal policy.

5. Conclusion

This study examined how income inequality, GDP growth, and sectoral public expenditure influence the Multidimensional Poverty Index (MPI) across 111 countries from 2010 to 2020 using fixed effects panel regression. Three main findings emerge. First, higher income inequality is associated with lower MPI in lower-middle and low-income countries (LMLICs: $\beta = -0.003$, $p<0.05$) but not in wealthier nations. This paradox arises because the Gini coefficient measures income dispersion while MPI captures health, education, and living standard deprivations; LMLICs such as Bangladesh, Kenya, and Vietnam expanded rural infrastructure during 2010-2020, reducing non-income poverty despite widening urban-rural income gaps. Second, GDP growth shows no significant direct effect on MPI in either country group, confirming that growth alone does not guarantee multidimensional poverty reduction. Third, sectoral spending effects are highly context-dependent. Agricultural expenditure reduces MPI in LMLICs but exhibits diminishing returns beyond approximately 3.2% of GDP, aligning with evidence that institutional bottlenecks limit absorptive capacity. Transport spending reduces MPI only in upper-middle and high-income countries ($\beta = -0.015$, $p<0.10$) by improving access to employment, education, and healthcare. Conversely, health spending in wealthier nations ($\beta = 0.016$, $p<0.10$) is counterproductive due to tertiary care bias that bypasses disadvantaged populations. Energy and social protection spending in LMLICs show positive MPI associations ($\beta = 0.020$ and 0.017, respectively, $p<0.05$), as energy subsidies are often regressive. Nigeria's fuel subsidy minimally benefited the poor and social protection programs suffer from leakage and elite capture, as documented in Bangladesh. This is among the first multi-country studies to simultaneously model MPI, inequality, growth, and seven categories of public expenditure across income groups, revealing that fiscal policy effects on multidimensional poverty are highly context-specific.

Policymakers in developing countries should redirect agricultural subsidies toward smallholder-friendly investments, reform fuel subsidies into targeted cash transfers, and strengthen social protection delivery systems. Wealthier nations should reallocate health spending from tertiary to primary and preventive care, and expand transport infrastructure in underserved areas.

However, this study has some limitations: (1) Potential endogeneity between poverty and spending (though lagged MPI partially addresses this); (2) Data limitations on sub-national MPI and expenditure disaggregation; (3) Omission of governance quality indicators; (4) 11-year window may not capture very long-term effects. Future research should incorporate institutional variables and use quasi-experimental methods. Future research should use quasi-experimental methods, incorporate governance indicators, and examine subnational variation to further elucidate how fiscal policy can maximize multidimensional poverty reduction.

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