PUBLIC SPENDING AND MULTIDIMENSIONAL POVERTY REDUCTION IN VIETNAM: AN ARDL APPROACH

PhD. Ha Thi Doan Trang* - Dang Ngoc Anh**

Abstract: ***Vietnam has achieved remarkable poverty reduction, with the multidimensional poverty rate declining from 28.2% in 2000 to 4.3% in 2025, driven significantly by expanded public spending on pro-poor programs. However, the differential effectiveness of spending components across infrastructure, education, health, and social assistance remains underexplored, limiting evidence-based fiscal planning. This study examines the short-run and long-run impacts of disaggregated public spending on multidimensional poverty in Vietnam over 2000-2025 using Autoregressive Distributed Lag (ARDL) bounds testing methodology. Results reveal that education spending exhibits the strongest long-run poverty-reducing effect, with an elasticity of -0.523 (p<0.01), followed by health at -0.487, infrastructure at -0.312, and social assistance at -0.215. Short-run dynamics differ substantially, as infrastructure generates immediate impacts while education effects materialize with a one-year lag. The error correction coefficient of -0.615 indicates that 61.5% of disequilibrium is corrected annually. Findings suggest that Vietnam should reallocate public spending toward education and health to accelerate poverty reduction toward Sustainable Development Goal 1: End poverty in all its forms everywhere targets.***

• Keywords: *public spending; multidimensional poverty; ARDL; Vietnam; poverty reduction.*

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1. Introduction

1.1. Background and Context

Vietnam has achieved remarkable progress in poverty reduction over the past two and a half decades, representing one of the most successful development stories in Southeast Asia. The multidimensional poverty rate declined dramatically from 28.2% in 2000 to 4.3% in 2025 (GSO, 2025), while GDP per capita increased from $390 to $4,700 over the same period (World Bank, 2025). This achievement has lifted millions of households out of poverty and positioned Vietnam as a lower-middle-income country with aspirations to reach high-income status by 2045.

A critical driver of this poverty reduction has been Vietnam's sustained expansion of public spending on pro-poor programs. Total government expenditure allocated to poverty alleviation increased from 45 trillion VND in 2000 to 320 trillion VND in 2025 at constant 2010 prices (Ministry of Finance, 2025). This spending encompasses four main components: infrastructure development, education and vocational training, health and social health insurance, and social assistance programs.

However, as Vietnam approaches the final phase of its poverty reduction agenda, policymakers face a critical question: which type of public spending delivers the highest poverty impact? This question has gained urgency amid fiscal consolidation pressures and the need to balance poverty reduction with other development priorities such as climate adaptation and digital transformation (World Bank, 2024).

1.2. Research Gap

Despite the policy importance of this question, existing empirical evidence on Vietnam remains limited in three key respects. First, previous studies examining the poverty impact of public spending have predominantly employed ordinary least squares (OLS) regression (Van de Walle & Gunewardena, 2001; Nguyen et al., 2007), which cannot distinguish between short-run and long-run effects or capture dynamic adjustment processes. This is critical, as human capital investments in education and health are theoretically expected to generate stronger effects in the long run, while infrastructure and cash transfers may have more immediate impacts.

Second, most existing research analyzes

** Academy of Finance; Corresponding author, email: hadoantrang@hvtc.edu.vn*
*** CQ61/01.03, Academy of Finance*

total public spending without decomposing the aggregate effect across infrastructure, education, health, and social assistance. This prevents comparative assessment of relative effectiveness and limits the ability to provide targeted reallocation guidance.

Third, time-series analysis of Vietnam's poverty-spending relationship remains scarce. Given Vietnam's structural transformation over 2000 to 2025, understanding temporal dynamics requires methods that accommodate non-stationary data and cointegration relationships.

To address these gaps, this study employs the Autoregressive Distributed Lag (ARDL) bounds testing approach, which offers three advantages: suitability for small samples (n=26), flexibility to handle mixed integration orders, and explicit separation of short-run dynamics from long-run equilibrium through the Error Correction Model framework (Pesaran et al., 2001).

1.3. Research Objectives

The primary objective is to examine the short-run and long-run impact of public spending on multidimensional poverty in Vietnam from 2000 to 2025, with explicit decomposition by spending type. Three research questions guide the analysis:

(1): What are the individual effects of infrastructure, education, health, and social assistance spending on poverty within a unified ARDL framework?

(2): Which spending component delivers the strongest poverty-reducing effect in both short and long run, and what is the lag structure through which effects materialize?

(3): How should Vietnam reallocate its poverty-reduction budget to maximize impact and align with Sustainable Development Goal 1?

1.4. Structure of the Paper

Section 2 reviews theoretical and empirical literature. Section 3 describes data, variables, and ARDL methodology. Section 4 presents unit root tests, cointegration analysis, and estimation results. Section 5 discusses economic interpretation and policy implications. Section 6 concludes with key contributions and future research directions.

2. Literature review

2.1. Theoretical Framework

The relationship between public spending and poverty reduction is grounded in three complementary theoretical frameworks. First, Human Capital Theory (Becker, 1964) posits that investments in education and health enhance individual productivity and earning capacity, creating sustainable pathways out of poverty. Unlike immediate consumption support, human capital accumulation generates long-term returns through improved labor market outcomes, intergenerational mobility, and reduced vulnerability to income shocks. This framework predicts that education and health expenditures should exhibit stronger long-run poverty impacts compared to short-term transfers.

Second, Public Goods Theory (Samuelson, 1954) emphasizes infrastructure as a prerequisite for economic activity. Rural roads, electricity, and clean water systems reduce transaction costs, expand market access, and enable productive asset utilization by poor households. Infrastructure investments create positive externalities that private markets under-provide, justifying public intervention. However, the poverty impact of infrastructure depends critically on complementary factors such as access to credit, skills, and functioning input markets.

Third, Sen's Capability Approach (1999) broadens the poverty concept beyond income to encompass multidimensional deprivations in health, education, and living standards. This framework justifies our use of Vietnam's multidimensional poverty measure, which captures not only household income but also access to basic services, dimensions directly targeted by public spending programs. Together, these theories suggest heterogeneous effects across spending types, with human capital investments generating deeper but delayed impacts, and infrastructure delivering more immediate but potentially transitory benefits.

2.2. International Evidence

Empirical evidence on the poverty impact of public spending can be organized into three methodological groups.

Group A: ARDL Studies. Several studies have employed ARDL bounds testing to examine spending-poverty dynamics in developing countries. Chaudhry et al. (2009) found that health spending had the strongest poverty-reducing effect in Pakistan, with a long-run elasticity of -0.42 compared to -0.28 for education. Odhiambo

(2009) demonstrated that education spending outperformed infrastructure in South Africa, with effects materializing after a two-year lag. Ijaiya et al. (2011) reported mixed results for Nigeria, attributing weak impacts to governance challenges and leakage in program implementation. These studies establish the value of ARDL for small-sample contexts but highlight considerable cross-country heterogeneity.

Group B: Panel Data Studies. Cross-country panel analyses using fixed effects and generalized method of moments provide broader insights. Gomanee et al. (2005) analyzed 25 developing countries and found that pro-poor public spending reduced poverty headcount by 0.8 percentage points for every 1% of GDP increase. Mosley et al. (2004) emphasized that spending quality, measured by governance indicators and targeting efficiency, mattered more than quantity in Sub-Saharan Africa. Arauco et al. (2014) documented the effectiveness of conditional cash transfer programs in Latin America, though effects weakened without complementary investments in service delivery. These studies underscore the importance of institutional context and program design.

Group C: Country-Specific Studies. Single-country analyses offer detailed institutional insights. Suryahadi et al. (2012) found that Indonesia's poverty decline during 2000 to 2010 was driven primarily by infrastructure expansion combined with education spending. Warr (2003) demonstrated that Thailand's agricultural spending had the highest poverty elasticity of -0.54 due to the concentration of poor households in rural areas. Ahmed and O'Donoghue (2010) showed that Bangladesh's microfinance programs and health initiatives jointly reduced poverty, with synergistic effects when implemented together. These studies highlight the need to align spending composition with country-specific poverty profiles.

2.3. Evidence from Vietnam

Vietnam-specific research has primarily relied on cross-sectional or short-panel methods. Van de Walle and Gunewardena (2001) used household survey data to show that road infrastructure improved market access and reduced ethnic poverty gaps, though effects were geographically heterogeneous. Nguyen et al. (2007) found that education and health spending had significant poverty impacts at the provincial level using OLS, but could not distinguish short-run from long-run dynamics. The World Bank (2012) evaluated Vietnam's social protection programs and concluded that targeted cash transfers were cost-effective for elderly and disabled populations but had limited impact on working-age poverty.

Recent studies have largely focused on specific programs such as scholarships, health insurance subsidies, or the National Target Program on Poverty Reduction without providing a comprehensive assessment of overall spending composition (Tran & Nguyen, 2018; Le et al., 2020). Critically, no existing study has employed ARDL methodology to decompose Vietnam's public spending into infrastructure, education, health, and social assistance components, and to examine both short-run and long-run poverty impacts using time-series data spanning 2000 to 2025. This represents a significant gap given Vietnam's rapid structural transformation and the methodological advantages of ARDL for capturing dynamic adjustment processes.

The present study addresses this gap by leveraging 26 years of annual data and ARDL bounds testing to provide the first comprehensive time-series analysis of Vietnam's poverty-spending relationship with explicit component decomposition. This approach allows identification of not only which spending type is most effective, but also the temporal structure of poverty responses, which provides critical information for fiscal planning in a resource-constrained environment.

3. Data and methodology

3.1. Data Sources

This study uses annual time-series data spanning 2000 to 2025, yielding 26 observations for econometric analysis. The dependent variable, multidimensional poverty rate (POV), is sourced from the General Statistics Office of Vietnam (GSO) and the Ministry of Home Affairs (MOHA). Vietnam's official multidimensional poverty measurement, introduced in 2016 and applied retrospectively, incorporates three dimensions: income below the national poverty line, access to basic social services, and deprivation in living standards. This approach aligns with the Alkire-Foster methodology and captures poverty breadth beyond monetary metrics.

Independent variables comprise four categories of public expenditure data obtained from the

Ministry of Finance's annual budget reports and reconciled with GSO fiscal statistics: infrastructure spending (G_INF), education spending (G_EDU), health spending (G_HLT), and social assistance (G_SOC). Control variables include GDP growth rate (GDPG) reflecting overall economic expansion, inflation (INF) measured by the Consumer Price Index annual change rate, and urbanization rate (URB) defined as the percentage of population residing in urban areas.

All monetary variables are expressed in constant 2010 prices using Vietnam's GDP deflator to ensure comparability across the 26-year period. Natural logarithm transformations are applied to spending variables to facilitate elasticity interpretation and reduce heteroskedasticity. The final dataset contains no missing observations, as Vietnam's statistical reporting has been comprehensive and consistent since 2000.

3.2. Variable Definition and Measurement

Table 1 provides detailed variable descriptions, measurement units, data sources, and expected signs based on theoretical priors discussed in Section 2.

Table 1: Variable Descriptions and Expected Signs

Variable	Definition	Unit	Source	Expected Sign
POV	Multidimensional poverty rate	%	GSO; MOLISA	Dependent variable
G_INF	Infrastructure spending (ln)	Trillion VND	Ministry of Finance	Negative (-)
G_EDU	Education spending (ln)	Trillion VND	Ministry of Finance	Negative (-)
G_HLT	Health spending (ln)	Trillion VND	Ministry of Finance	Negative (-)
G_SOC	Social assistance (ln)	Trillion VND	Ministry of Finance	Negative (-)
GDPG	GDP growth rate	%	GSO	Negative (-)
INF	Inflation rate (CPI change)	%	GSO	Positive (+)
URB	Urbanization rate	%	GSO	Negative (-)

Source: Authors' compilation

The expected negative signs for all spending variables reflect the theoretical prediction that increased public expenditure reduces poverty. GDPG is expected to be negative reflecting pro-poor growth, while INF is expected positive as inflation erodes real income of the poor. URB is expected negative as urbanization expands non-agricultural employment opportunities.

3.3. Econometric Strategy

Given the time-series nature of our data, we employ a four-step econometric procedure to ensure robust inference and avoid spurious regression problems common in non-stationary series.

3.3.1. Unit Root Testing

We first test for stationarity using the Augmented Dickey-Fuller (ADF) test at both levels and first differences for all variables. The ADF test examines the null hypothesis H_0: the series contains a unit root (non-stationary) against the alternative H_1: the series is stationary. The test regression includes a constant and trend term where appropriate, with lag length determined by the Schwarz Information Criterion (SIC). We reject H_0 if the p-value < 0.05, indicating stationarity. Variables stationary at levels are classified as I(0), while those requiring first-differencing to achieve stationarity are classified as I(1).

3.3.2. Cointegration Testing

If variables exhibit mixed integration orders I(0) and I(1), we proceed with the Engle-Granger two-step cointegration test. This involves: (i) estimating the long-run equilibrium relationship via OLS, and (ii) applying the ADF test to the residuals. If residuals are stationary ($p < 0.05$), we confirm cointegration (indicating that despite individual non) stationarity, the variables share a common long-run equilibrium path. This justifies the ARDL framework.

3.3.3. ARDL Model Specification

We estimate two ARDL models. Model 1 examines aggregate public spending effects:

$$\Delta POV_t = \alpha_0 + \Sigma_{i=1}^{p} \alpha_i \Delta POV_{t-i} + \Sigma_{j=0}^{g} \beta_j \Delta G_{t-j} + \Sigma_{k=0}^{r} \gamma_k \Delta X_{t-k} + \lambda ECT_{t-1} + \varepsilon_t$$

Model 2 disaggregates spending into four components:

$$\Delta POV_t = \alpha_0 + \Sigma_i \alpha_i \Delta POV_{t-i} + \Sigma_j \beta_{1j} \Delta G_INF_{t-j} + \Sigma_j \beta_{2j} \Delta G_EDU_{t-j} + \Sigma_j \beta_{3j} \Delta G_HLT_{t-j} + \Sigma_j \beta_{4j} \Delta G_SOC_{t-j} + \Sigma_k \gamma_k \Delta X_{t-k} + \lambda ECT_{t-1} + \varepsilon_t$$

where Δ denotes the first-difference operator, ECT is the Error Correction Term measuring deviations from long-run equilibrium, and λ is the speed of adjustment coefficient (expected $-1 < \lambda < 0$). A significant negative λ confirms error-correction dynamics: when poverty deviates from its long-run equilibrium, it adjusts back at speed $|\lambda|$ per period.

Optimal lag lengths (p, q, r) are selected using Akaike Information Criterion (AIC) and Schwarz-Bayesian Criterion (SBC), balancing model fit against parsimony given our small sample (n=26). The ARDL bounds testing approach developed by Pesaran et al. (2001) allows joint estimation of short-run coefficients (Δ terms) and long-run coefficients (derived from level variables), while accommodating mixed I(0)/I(1) regressors without imposing pre-testing restrictions.

3.3.4. Diagnostic Tests

To validate model specification, we conduct three diagnostic checks: (i) Breusch-Godfrey LM test for serial correlation (H_0: no autocorrelation), (ii) White test for heteroskedasticity (H_0: homoskedastic errors), and (iii) CUSUM test for parameter stability across the sample period. Models passing all diagnostics ensure reliable inference.

3.4. Estimation Software

All estimations are performed using STATA 17. Key commands include: dfuller for ADF unit root tests, varsoc for optimal lag selection, ardl with bounds option for ARDL bounds testing, and ardl, ec for extracting Error Correction Model parameters. Diagnostic tests employ estat bgodfrey, estat imtest, and cusum routines. This computational approach ensures transparency and replicability.

4. Empirical results

4.1. Descriptive Statistics

Table 2 presents summary statistics for all variables over the 2000 to 2025 period. The multidimensional poverty rate declined from 28.2% in 2000 to 4.3% in 2025, representing an 84.8% reduction that confirms Vietnam's remarkable poverty alleviation achievement. Among spending categories, education spending demonstrates the highest average level and most consistent growth trajectory, while infrastructure spending exhibits the greatest variation, reflecting cyclical patterns driven by five-year development plans. Social assistance remains the smallest component but shows proportionally strong expansion following the revised poverty line adoption in 2015. GDP growth averaged a robust 6.2% annually, though inflation volatility was notable during the 2008 to 2011 period.

Table 2: Descriptive Statistics (2000-2025, n=26)

Variable	Mean	Std. Dev.	Min	Max
POV (%)	12,5	8,3	4,3	28,2
G_INF (Trillion VND)	45,2	15,8	22,3	78,5
G_EDU (Trillion VND)	52,8	18,2	28,1	89,4
G_HLT (Trillion VND)	38,6	13,5	19,7	68,2
G_SOC (Trillion VND)	24,3	9,8	11,2	45,6
GDPG (%)	6,2	1,4	2,6	8,5
INF (%)	5,8	4,2	0,6	18,7
URB (%)	32,4	5,7	24,3	42,1

Note: All monetary values in constant 2010 prices. Source: Authors' calculations from GSO and MOF data.

4.2. Unit Root Test Results

Table 3 reports ADF test statistics for all variables at levels and first differences. At the 5% significance level, all variables fail to reject the unit root null hypothesis in levels, with p-values exceeding 0.05, indicating non-stationarity. However, first-differencing renders all series stationary, with p-values well below 0.01. This confirms that all variables are integrated of order one, denoted as I(1).

Table 3: Augmented Dickey-Fuller Unit Root Test Results

Variable	Level	p-value	First Difference	p-value	Integration
POV	-2.15	0.231	-4.82***	0.001	I(1)
G_INF	-1.98	0.289	-5.21***	0.000	I(1)
G_EDU	-2.08	0.256	-5.34***	0.000	I(1)
G_HLT	-1.87	0.342	-4.95***	0.001	I(1)
G_SOC	-2.23	0.198	-5.08***	0.000	I(1)
GDPG	-2.45	0.134	-6.12***	0.000	I(1)
INF	-2.67	0.085	-5.78***	0.000	I(1)
URB	-1.76	0.398	-4.67***	0.002	I(1)

*Note: ADF test includes constant and trend. *** p<0.01, ** p<0.05, * p<0.10.*

The uniform I(1) classification makes the dataset ideal for ARDL bounds testing, which accommodates I(0) and I(1) variables but not I(2). Following Pesaran et al. (2001), we proceed with cointegration analysis. The Engle-Granger test on residuals from the long-run relationship yields an ADF statistic of -4.85 with a p-value of 0.002, rejecting the null of no cointegration at the 1% level. This confirms a stable long-run equilibrium relationship between public spending and poverty, validating the ARDL specification.

4.3. ARDL Model 1 Results: Aggregate Public Spending

Table 4 presents estimation results for Model 1, which treats total poverty reduction spending as an aggregate variable. Optimal lag selection via AIC yields ARDL(2,1,1,0,0) specification with two lags for the dependent variable, one lag each for total spending and GDP growth, and contemporaneous effects for inflation and urbanization.

Table 4: ARDL Estimation Results: Aggregate Public Spending Model

Panel A: Long-Run Coefficients

Variable	Coefficient	Std. Error	t-statistic	p-value
G (total)	-0.453***	0.112	-4.04	0.001
GDPG	-0.321**	0.145	-2.21	0.038
INF	0.186*	0.098	1.90	0.072
URB	-0.267**	0.128	-2.09	0.049
Constant	8.452***	2.134	3.96	0.001

Panel B: Short-Run Coefficients (Error Correction Model)

Variable	Coefficient	Std. Error	t-statistic	p-value
ΔG	-0.182**	0.078	-2.33	0.029
ΔGDPG	-0.148*	0.082	-1.81	0.085
ΔINF	0.095	0.067	1.42	0.171
ΔURB	-0.112	0.089	-1.26	0.222
ECT(t-1)	-0.615***	0.124	-4.96	0.000

*Note: *** p<0.01, ** p<0.05, * p<0.10. Diagnostic tests: Breusch-Godfrey LM (p=0.342), White test (p=0.298), CUSUM stable.*

The long-run coefficient for total public spending is -0.453 with p=0.001, indicating that a 1% increase in poverty reduction expenditure reduces multidimensional poverty by 0.45% in equilibrium, a substantial and highly significant effect. GDP growth exhibits the expected negative sign of -0.321 with p=0.038, confirming pro-poor growth dynamics. Inflation positively affects poverty at 0.186 with p=0.072, as price increases erode real incomes of vulnerable households. Urbanization reduces poverty with a coefficient of -0.267 and p=0.049 through expanded labor market opportunities.

Short-run dynamics reveal an immediate spending effect of -0.182 with p=0.029, smaller than the long-run impact, suggesting gradual poverty response as programs scale up and behavioral changes materialize. The Error Correction Term coefficient of -0.615 with p<0.001 indicates that 61.5% of any disequilibrium is corrected within one year, a relatively rapid adjustment speed reflecting Vietnam's effective implementation capacity. All diagnostic tests confirm model validity with no serial correlation detected at p=0.342, homoskedastic errors at p=0.298, and stable parameters confirmed by CUSUM test.

While Model 1 establishes the aggregate poverty impact of public spending, it does not reveal which specific component, whether infrastructure, education, health, or social assistance, drives this effect. We now turn to Model 2, which decomposes total spending into its four constituent categories to identify relative effectiveness and inform fiscal reallocation strategies.

4.4. ARDL Model 2 Results: Decomposed Public Spending

Table 5 presents results from Model 2, which disaggregates total spending into its four constituent components. The optimal specification selected by AIC is ARDL (2,1,2,1,1,1,0,0), allowing differential lag structures across spending types while maintaining parsimony given the small sample constraint.

Table 5: ARDL Estimation Results: Decomposed Public Spending Model

Panel A: Long-Run Coefficients

Variable	Coefficient	Std. Error	t-statistic	p-value	Rank
G_EDU	-0.523***	0.135	-3.87	0.001	1
G_HLT	-0.487***	0.142	-3.43	0.003	2
G_INF	-0.312**	0.128	-2.44	0.024	3
G_SOC	-0.215*	0.118	-1.82	0.083	4
GDPG	-0.298**	0.138	-2.16	0.043	-
INF	0.175*	0.095	1.84	0.080	-
URB	-0.241**	0.121	-1.99	0.060	-

Panel B: Short-Run Coefficients (Error Correction Model)

Variable	Coefficient	Std. Error	t-statistic	Dynamics
ΔG_EDU(t)	-0.098	0.089	-1.10	Lagged
ΔG_EDU(t-1)	-0.215**	0.094	-2.29	1-year lag
ΔG_HLT(t)	-0.142*	0.082	-1.73	Immediate
ΔG_INF(t)	-0.187**	0.076	-2.46	Immediate
ΔG_SOC(t)	-0.103	0.085	-1.21	Weak
ECT(t-1)	-0.638***	0.128	-4.98	-

*Note: *** p<0.01, ** p<0.05, * p<0.10. Control variables included but not reported for brevity.*

Key findings emerge from the decomposed analysis. First, education spending exhibits the strongest long-run poverty impact with an elasticity of -0.523 and p=0.001, indicating that a 1% increase in education expenditure reduces poverty by 0.52% in equilibrium. This aligns with human capital theory, as investments in schooling, vocational training, and skills development create sustainable income generation pathways for poor households. Notably, the short-run effect appears with a one-year lag at -0.215 for t-1, reflecting the time required for educational attainment to translate into labor market outcomes.

Second, health spending ranks a close second with -0.487 and p=0.003, confirming its critical role in poverty reduction through multiple channels including preventing catastrophic health expenditures, improving labor productivity, and reducing child mortality. Unlike education, health spending shows an immediate short-run effect of -0.142 with p=0.080, likely driven by preventive care programs and health insurance subsidies that provide instant financial relief.

Third, infrastructure spending demonstrates moderate long-run effectiveness at -0.312 with p=0.024 but exhibits the strongest immediate impact in the short run at -0.187 with p=0.024. This pattern suggests that rural roads and electrification quickly expand market access and create construction employment, but these gains are less transformative than human capital

accumulation in the long term, consistent with findings from Indonesia (Suryahadi et al., 2012) and Thailand (Warr, 2003).

Fourth, social assistance shows the weakest effect at -0.215 with p=0.083, significant only at the 10% level. While cash transfers provide important consumption smoothing for vulnerable groups, they do not generate the structural income increases produced by education and health investments. The insignificant short-run coefficient of -0.103 with p=0.233 suggests that transfer amounts may be too modest to measurably shift poverty status immediately.

The Error Correction Term of -0.638 with p<0.001 indicates slightly faster adjustment in the decomposed model compared to Model 1, with 63.8% of disequilibrium corrected annually. All control variables retain expected signs and remain statistically significant.

4.5. Diagnostic Tests

Table 6 summarizes diagnostic test results for both models, confirming the validity of our ARDL specifications.

Table 6: Diagnostic Test Results

Test	Model 1	Model 2	Null Hypothesis (H_0)	Decision
Breusch-Godfrey LM	χ^2=2·15 (p=0·341)	χ^2=2·28 (p=0·320)	No serial correlation	Accept H_0
White Test	χ^2=18.42 (p=0.298)	χ^2=22.15 (p=0.275)	Homoskedastic errors	Accept H_0
CUSUM	Stable	Stable	Parameter stability	Stable
Ramsey RESET	F=1.82 (p=0.195)	F=2.01 (p=0.175)	Correct functional form	Accept H_0

Note: All tests conducted at 5% significance level.

Both models pass all diagnostic checks. The Breusch-Godfrey LM test fails to detect serial correlation with p>0.05, confirming that error terms are not autocorrelated. The White test accepts homoskedasticity with p>0.05, validating our standard error estimates. CUSUM plots remain within critical bounds, indicating stable parameters throughout 2000 to 2025 despite structural changes in Vietnam's economy. The Ramsey RESET test confirms correct functional form specification. These results ensure that our inference is robust and policy recommendations are credible.

The empirical findings from Models 1 and 2 establish both the aggregate poverty impact of public spending and the differential effectiveness of its components. We now interpret these results in the context of Vietnam's policy environment and develop concrete recommendations for fiscal reallocation to maximize poverty reduction outcomes over the 2026 to 2030 planning horizon.

5. Discussion and policy implications

5.1. Interpretation of Findings

Our empirical results yield four principal findings that inform fiscal policy design for sustainable poverty reduction in Vietnam.

Finding 1: Education spending exhibits the strongest poverty-reducing effect. With a long-run elasticity of -0.523, education outperforms all other spending categories, consistent with human capital theory (Becker, 1964). This result aligns with evidence from Thailand (Warr, 2003) and Indonesia (Suryahadi et al., 2012), where education investments generated the highest poverty returns. The mechanism operates through multiple channels: primary education provides foundational literacy and numeracy, vocational training equips poor youth with marketable skills, and tuition exemptions prevent intergenerational poverty transmission by keeping children in school. Notably, the one-year lag structure confirms that educational investments require time to translate into labor market outcomes. Graduates must complete programs, acquire credentials, and secure employment before household income rises. This delayed but powerful effect underscores education as a long-term poverty solution rather than a quick fix.

Finding 2: Health spending demonstrates strong long-run effectiveness. The elasticity of -0.487 reflects health's dual role in poverty reduction. First, subsidized health insurance and preventive care prevent catastrophic medical expenditures, a leading cause of poverty relapse in Vietnam (Wagstaff & van Doorslaer, 2003). Second, improved health status enhances labor productivity and reduces income loss from illness, particularly for manual laborers in agriculture and construction. Third, nutrition programs and maternal care reduce child mortality and stunting, building human capital from early childhood. The immediate short-run effect of -0.142 contrasts with education's delayed impact, as health insurance coverage provides instant financial protection. These findings support Sen's (1999) capability approach, which argues that health enables individuals to convert resources into wellbeing and economic opportunities.

*Finding 3: Infrastructure spending yields immediate but moderate poverty impacts***.** While the long-run coefficient of -0.312 is substantial, it ranks below human capital investments. This pattern reflects infrastructure's dual nature.

Rural roads and electrification quickly create construction jobs and expand market access, explaining the strong immediate effect of -0.187, but do not fundamentally alter household earning capacity unless combined with complementary investments in skills and health. This confirms Van de Walle and Gunewardena's (2001) finding that Vietnam's rural infrastructure reduced ethnic poverty gaps by improving market integration, though effects were geographically uneven. Infrastructure serves as an enabler rather than a driver of long-term poverty exit, consistent with cross-country evidence showing that roads without schools yield limited poverty reduction (Gomanee et al., 2005).

*Finding 4: Social assistance shows the weakest but still significant effect***.** The coefficient of -0.215 with p=0.083 indicates that cash transfers and housing support provide valuable consumption smoothing for vulnerable groups such as elderly, disabled, and ethnic minorities unable to participate in labor markets, but do not generate structural income increases. This distinguishes social protection from human capital investments, as transfers address current deprivation without building future earning capacity. However, the modest magnitude suggests two concerns. First, benefit levels may be insufficient to lift recipients above the poverty line. Second, unconditional transfers lack incentives for behavioral change. These limitations motivate our recommendation to reform social assistance toward conditional and graduation-oriented programs.

5.2. Policy Implications

Based on these findings, we propose four policy recommendations for Vietnam's fiscal planning horizon 2026 to 2030.

Recommendation 1: Reallocate public spending toward education and health. Current budget allocation dedicates approximately 32% to infrastructure, 28% to education, 22% to health, and 18% to social assistance. Our elasticity estimates suggest rebalancing toward education at 35% (an increase of 7 percentage points), health at 30% (an increase of 8 percentage points), infrastructure at 25% (a decrease of 7 percentage points), and social assistance at 10% (a decrease of 8 percentage points). Simulation using our coefficients predicts this reallocation could achieve an additional 1.2 to 1.5 percentage point poverty reduction by 2030 beyond the baseline trajectory, equivalent to lifting 350,000 to 450,000 individuals out of poverty. Crucially, this reallocation need not reduce absolute infrastructure spending, as nominal increases can be slower than for education and health, allowing gradual compositional shifts without disrupting ongoing projects.

Recommendation 2: Improve efficiency of infrastructure spending. Rather than reducing infrastructure budgets sharply, focus on better targeting. Prioritize rural roads linking poor communes to district markets and provincial centers, as market access multiplies returns to agricultural production. Co-locate infrastructure with social facilities by positioning health stations and schools near new road networks to maximize synergies. Implement rigorous cost-benefit analysis using poverty impact as a key criterion, phasing out low-return projects such as urban beautification in favor of high-return rural connectivity investments.

Recommendation 3: Reform social assistance toward graduation programs. Transition from unconditional cash transfers to conditional programs linking support to productive behaviors. Require transfer recipients to participate in vocational training, adult literacy programs, or microenterprise development. Adopt Bangladesh's BRAC graduation model, which combines consumption support with asset transfers such as livestock and tools, skills training, and savings mobilization to enable households to graduate from assistance within 18 to 24 months (Bandiera et al., 2017). Pilot these reforms in 10 to 15 provinces during 2026 to 2027 before national rollout.

Recommendation 4: Implement phased fiscal planning. A three-phase roadmap ensures smooth transition. Phase 1 covering 2026 to 2027 focuses on policy framework by revising budget classification to align with spending effectiveness rankings, establishing inter-ministerial coordination mechanisms, and piloting conditional transfer programs. Phase 2 covering 2028 to 2029 implements reallocation by gradually shifting budget shares as outlined in Recommendation 1, scaling successful pilots nationwide, and strengthening monitoring and evaluation systems. Phase 3 in 2030 conducts comprehensive evaluation using updated poverty data and refines strategies based on outcomes. This gradual approach minimizes disruption while building political consensus.

5.3. Limitations

Four limitations warrant acknowledgment. First, our small sample of 26 observations constrains degrees of freedom, limiting the number of control variables and lag structures we can include. Longer time series would enable more robust specifications. Second, national-level aggregation masks regional heterogeneity. Poverty dynamics in the Mekong Delta differ from the Northern Mountains, yet our model assumes uniform effects. Provincial panel data would reveal spatial variation. Third, we assume linear relationships, but poverty impacts may exhibit non-linearities such as threshold effects where spending becomes effective only above certain levels. Fourth, omitted variables, particularly governance quality, corruption, and targeting efficiency, likely influence spending effectiveness but are difficult to quantify in time-series frameworks. These limitations suggest directions for future research while not invalidating our core findings, which rest on strong theoretical foundations and align with international evidence.

Conclusion

This study has examined the short-run and long-run impacts of public spending on multidimensional poverty in Vietnam over the period 2000 to 2025, employing ARDL bounds testing methodology with explicit decomposition by spending type. Our analysis establishes that education spending exhibits the strongest poverty-reducing effect with a long-run elasticity of -0.523, followed by health at -0.487, infrastructure at -0.312, and social assistance at -0.215. Notably, education effects materialize with a one-year lag while health and infrastructure generate immediate impacts, revealing differential temporal patterns critical for multi-year budget planning. The error correction coefficient of -0.615 indicates that 61.5% of any disequilibrium is corrected annually, reflecting relatively rapid adjustment dynamics.

This study makes three contributions to the literature. First, it represents the first Vietnam-specific application of ARDL methodology to decompose public spending into four components using complete time-series data spanning 2000 to 2025. Second, it provides rigorous quantitative evidence to guide fiscal reallocation decisions, moving beyond qualitative assessments or cross-sectional correlations. Third, it explicitly separates short-run adjustment dynamics from long-run equilibrium relationships, revealing that human capital investments generate stronger but delayed effects compared to infrastructure and transfers.

The policy message is clear: Vietnam should reallocate public spending toward education and health to accelerate poverty reduction toward SDG 1 targets. Our simulations suggest that increasing education's budget share to 35% and health's share to 30%, while maintaining infrastructure at 25% and reducing social assistance to 10%, could accelerate poverty decline by 1.2 to 1.5 percentage points beyond baseline projections by 2030. This reallocation need not reduce absolute infrastructure spending but rather moderates its growth rate relative to human capital investments.

Future research should address three extensions. First, provincial panel data analysis would reveal geographic heterogeneity in spending effectiveness, enabling spatially targeted policies. Second, threshold regression models could identify non-linear effects where spending becomes effective only above certain levels. Third, incorporating governance quality and targeting efficiency as moderating variables would illuminate why similar spending levels produce different poverty outcomes across regions and time periods.

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