“Public education expenditure and income inequality in Vietnam: The moderating role of institutional quality”

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PUBLIC EDUCATION EXPENDITURE AND INCOME INEQUALITY IN VIETNAM: THE MODERATING ROLE OF INSTITUTIONAL QUALITY

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Abstract

Income inequality remains a major challenge for inclusive development, particularly in emerging economies where fiscal policy plays a central role in redistributing income opportunities. This study examines how public education expenditure affects income inequality across Vietnam's 63 provinces over the period 2011–2024 and whether institutional quality moderates this relationship under spatial dependence. Using panel and spatial econometric approaches, with the Spatial Durbin Model (SDM) as the primary specification, the analysis captures both within-province effects and interprovincial spillovers. The results show that public education expenditure is positively associated with income inequality in the short- to medium-term. A 1% increase in education spending raises the Gini coefficient by approximately 0.067-0.157 percentage points within provinces, with larger spillover effects observed across neighboring provinces. However, institutional quality significantly mitigates this effect. Interaction variables based on the Provincial Competitiveness Index (PCI) and the Public Administration Performance Index (PAPI) are negative and statistically significant, indicating that stronger institutional quality dampens the inequality-increasing effect of education expenditure. The findings also confirm that spatial dependence is pronounced, and education spending generates meaningful spillovers, indicating that inequality outcomes in one province are partly shaped by spending patterns in neighboring provinces. Overall, the findings suggest that expanding education budgets alone is unlikely to deliver equitable outcomes without parallel reforms that strengthen transparency, accountability, and performance-based allocation, alongside regional coordination to manage spatial externalities.

Keywords education expenditure, inequality, spatial regression, institutions, Vietnam

JEL Classification I24, D63, C33, H52

INTRODUCTION

Income inequality has become a central challenge for inclusive and sustainable development, particularly in developing economies undergoing rapid structural transformation. While economic growth has lifted millions out of poverty, disparities in income distribution persist and, in some cases, have widened, raising concerns about social cohesion and long-term development prospects instability (Alesina et al., 2016; Ferrer-i-Carbonell et al., 2014; Østby, 2013).

Vietnam provides a compelling context for examining these issues. Since the Doi Moi reforms, the country has undergone rapid and sustained economic transformation. GDP per capita reached approximately USD 4,700 by 2024, and poverty has fallen dramatically, with the national multidimensional poverty rate dropping to about 1.9 percent. However, income inequality remains evident across provinces and population groups, reflecting uneven development patterns, dif-

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ferences in access to education and labor markets, and persistent regional disparities (World Bank, 2022). These imbalances pose important challenges for achieving inclusive growth.

Public education expenditure is widely regarded as a key policy instrument for promoting equitable development by enhancing human capital and expanding economic opportunities (Barro, 1990; Becker, 1964; Mincer, 1974). In Vietnam, education has consistently accounted for a substantial share of public expenditure, reflecting the government's long-standing commitment to human capital development. However, whether such spending translates into a more equitable distribution of income depends on the conditions under which it is implemented. Provincial differences in institutional quality may affect how efficiently public resources are allocated and delivered, while strong interprovincial linkages suggest that the effects of education spending may spill across administrative boundaries.

Against this backdrop, an important question is whether public education expenditure can reduce income inequality across Vietnamese provinces, and how this relationship is influenced by institutional quality and spatial spillovers. This question is especially important in a decentralized and spatially interconnected economy, where the distributive effects of public spending may depend not only on local fiscal decisions but also on the broader institutional and regional context.

1. LITERATURE REVIEW AND HYPOTHESES

Income inequality has long been a global concern, as persistent disparities can weaken social cohesion, limit economic opportunity, and undermine sustainable development. In this context, the distributional effects of public expenditure have become a focal issue in public finance. Among its components, education spending is widely regarded as a key policy instrument for promoting a more equitable distribution of income (Galor & Zeira, 1993; Sylwester, 2002).

1.1. Public education expenditure and income inequality

The relationship between public education expenditure and income inequality has been widely discussed in both theoretical and empirical literature, yet remains inconclusive. On the one hand, human capital theory suggests that investment in education enhances individual productivity and lifetime earnings, thereby contributing to a more equal income distribution (Becker, 1964; Hanushek & Woessmann, 2008; Mincer, 1974). Similarly, endogenous growth models emphasize the role of education in fostering long-term economic development and improving welfare outcomes, particularly for lower-income individuals (Barro, 1990; Lucas Jr, 1988). On the other hand, public spending on education is a redistributive tool that helps expand access to basic services and lowers barriers to upward mobility (Atkinson & Stiglitz, 2015; Musgrave, 1959). Related contributions in growth and development economics similarly emphasize that human capital accumulation through education can improve long-run welfare and poverty outcomes, thereby reducing inequality (Collin & Weil, 2020; Lucas Jr, 1988).

However, the distributional impact of education expenditure is not yet equalizing. Its effect depends critically on how resources are allocated and who ultimately benefits. When public spending is directed toward primary and basic education, particularly for disadvantaged groups, it tends to reduce inequality. In contrast, when spending is concentrated on higher education or disproportionately benefits wealthier households and regions, it may reinforce existing disparities (Davoodi et al., 2010; Galor & Zeira, 1993; Lustig, 2018; Psacharopoulos & Patrinos, 2018). This distinction highlights the importance of spending composition and targeting in determining redistributive outcomes.

Empirical evidence also reflects this ambiguity. Several cross-country and country-specific studies find that increased education expenditure is associated with lower income inequality, largely through improved human capital accumulation and intergenerational mobility (Gregorio & Lee, 2002; Sylwester, 2002). Conversely, other studies report nonlinear or even inequality-increasing ef-

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fects. For example, Artige and Cavenaile (2023) show that higher education spending can widen inequality in certain U.S. states, while Voto and Ngepah (2024) identify an inverted U-shaped relationship in Sub-Saharan Africa. In a similar vein, Köse and Güven (2007) suggest that government expenditure on higher education tends to worsen income distribution in Türkiye. These mixed findings imply that the impact of education spending is highly context-dependent and influenced by structural and institutional conditions.

1.2. Institutional quality and the effectiveness of public spending

Another growing body of literature emphasizes that the effectiveness of public expenditure depends not only on the level of spending but also on the quality of institutions that govern its allocation and implementation. Institutions influence fiscal outcomes through mechanisms such as accountability, transparency, bureaucratic efficiency, and control of corruption (Acemoglu et al., 2014; Savoia et al., 2010; Supriono et al., 2023; Bilan et al., 2025). Recent evidence further suggests that the distributive effects of public education expenditure may also depend on wider macroeconomic constraints. For example, Mbewe et al. (2025) show that the inequality-reducing effect of public education expenditure in developing countries is contingent on the level of public debt, with education spending becoming less effective once debt rises beyond a critical threshold. This finding reinforces the broader argument that the impact of public spending is conditional rather than automatic (Kpegba et al., 2024).

Weak institutional environments may lead to resource misallocation, leakage, and elite capture, thereby limiting the benefits of public investment for disadvantaged groups (Gupta et al., 2002; Makuta & O'Hare, 2015; Rajkumar & Swaroop, 2008). As a result, public education expenditure may fail to achieve its intended redistributive objectives and may even exacerbate inequality. In contrast, stronger institutions can improve budget discipline, enhance targeting, and ensure more effective service delivery, thereby increasing the likelihood that public spending contributes to more equitable outcomes.

Empirical studies provide support for the moderating role of institutions. Doumbia and Kinda (2019) show that higher institutional quality enhances the poverty-reducing impact of public spending, while Kyriacou and Roca-Sagalés (2019) find that better governance strengthens the redistributive impact of fiscal policy. These findings suggest that institutional quality is a critical factor in determining whether education expenditure translates into decreased inequality, highlighting the need to incorporate institutional dimensions into empirical analyses.

1.3. Spatial interdependence and spillover effects

Beyond institutional factors, recent literature highlights the importance of spatial interdependence in shaping economic and social outcomes. Regional economies are linked through labor mobility, trade, capital flows, fiscal interactions, and knowledge diffusion, so conditions and policy interventions in one region can affect neighboring areas rather than remaining confined within administrative borders (Anselin et al., 2000; Meliciani & Peracchi, 2006; Ertur & Koch, 2007). This perspective is especially relevant to the analysis of income inequality, as it tends to cluster geographically (Curtis et al., 2012).

Such clustering suggests that social outcomes are shaped not only by local characteristics but also by spillovers from surrounding regions. In the case of public education expenditure, the spillovers may arise when improvements in educational infrastructure or services in one province attract students, skilled workers, or related investment from nearby provinces, thereby influencing income distribution across a wider geographic area (Wang et al., 2022). Consequently, conventional econometric models that ignore spatial dependence may produce biased or incomplete estimates of policy effects (Le Gallo et al., 2003; Otieno, 2024).

The above insights are particularly relevant in a decentralized economic system, where subnational policies often interact across jurisdictions. To account for such interdependence, spatial econometric approaches explicitly model regional linkages and distinguish between direct effects within a region and indirect spillover effects across regions (Anselin, 1988; Anselin, 1991; LeSage & Pace, 2009). This approach, for example, allows public education expenditure in one province to affect inequality both locally and in neighboring provinces.

1.4. Vietnamese evidence and research gap

In Vietnam, income inequality remains a significant development challenge despite substantial progress in poverty reduction and economic growth. Persistent disparities continue to exist across regions and social groups, particularly between the Kinh majority and ethnic minorities (Bui et al., 2017; Cuong et al., 2015; Nguyen et al., 2017). Recent evidence further shows that inequality in Vietnam is multidimensional and that interprovincial disparities account for a substantial share of total inequality (Dang et al., 2022). Other studies likewise document pronounced spatial differences in poverty and welfare across localities, suggesting that place-based disadvantage remains an important feature of Vietnam's development process (Cuong et al., 2010; Lanjouw et al., 2017; World Bank, 2022). If left unaddressed, such disparities may weaken inclusive growth and reduce the effectiveness of national poverty-reduction strategies (Nguyen & Pham, 2018; Lam, 2017).

Emerging evidence also suggests that provincial outcomes in Vietnam exhibit significant spatial autocorrelation and cross-provincial spillovers (Dinh Thanh et al., 2023). Provinces, therefore, do not operate in isolation; rather, their development trajectories are shaped by both local conditions and interactions with adjacent peers. Yet the existing literature on Vietnam has largely focused either on the determinants of inequality or on regional disparities themselves, without explicitly examining the distributional effects of public education expenditure.

Two further limitations are especially notable. First, limited attention has been paid to whether the impact of public education expenditure depends on institutional quality, even though governance conditions may shape how public resources are allocated and translated into distributional outcomes. Second, few studies have incorporated spatial interdependence explicitly, despite clear evidence that Vietnamese provinces are economically interconnected and that policy effects may spill across provincial borders. Accordingly, three gaps remain in the literature: the effect of public education expenditure on inequality remains ambiguous and context-dependent; the moderating role of institutional quality has not been adequately examined at the subnational level; and spatial spillover effects are often neglected.

To address these gaps, the present study investigates how public education expenditure affects income inequality across Vietnam's provinces, while explicitly accounting for the moderating role of institutional quality and the presence of spatial dependence. By integrating fiscal, institutional, and spatial dimensions within a unified empirical framework, the study provides a more comprehensive understanding of the conditions under which public education spending can contribute to more equitable development. The proposed conceptual framework (Figure 1) illustrates the potential interactions among these elements.

Based on the above discussions about theoretical development and empirical evidence, we propose the following hypotheses:

H1: *Public education expenditure significantly influences income inequality.*

H2: *Institutional quality moderates the relationship between public education expenditure and income inequality, controlling for socio-economic factors.*

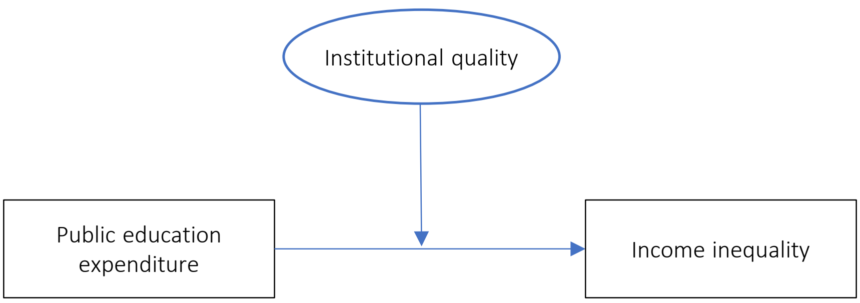

Figure 1. Conceptual framework

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2. METHODS

Spatial econometric models are particularly appropriate when socio-economic outcomes are spatially interconnected, and policy effects are not confined to administrative boundaries (Elhorst, 2014). To assess whether such spatial dependence characterizes the data, the analysis begins with Global Moran's I, which tests whether the dependent variable displays systematic spatial clustering. A positive and statistically significant Moran's I indicates that similar values tend to cluster together, such as high-high or low-low patterns, whereas a negative value suggests dispersion. This global measure is complemented by Local Indicators of Spatial Association (LISA), which identify local clusters and spatial outliers and thus provide a more fine-grained view of the spatial structure of inequality.

Following Belotti et al. (2017), spatial dependence can be incorporated into regression analysis through models such as the Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), the Spatial Durbin Model (SDM), and the more general General Nesting Spatial (GNS) model. SAR, SEM, and SDM are nested within the GNS framework, which can be written as follows:

GNS model:

$$y_{i,t} = \rho X_{i,t} + \beta_1 W_{ij} y_{i,t} + \beta_2 W_{ij} X_{i,t} + u_{i,t}, \quad (u_{it} = \theta W_u + \varepsilon), \tag{1}$$

SDM model:

$$y_{i,t} = \rho X_{i,t} + \beta_1 W_{ij} y_{i,t} + \beta_2 W_{ij} X_{i,t} + \varepsilon, \tag{2}$$

SAR model:

$$y_{i,t} = \rho X_{i,t} + \beta W_{ij} y_{i,t} + \varepsilon, \tag{3}$$

SEM model:

$$y_{i,t} = \rho X_{i,t} + u_{i,t}, \quad (u_{it} = \theta W_u + \varepsilon), \tag{4}$$

SAC model:

$$y_{i,t} = \rho X_{i,t} + \hat{a}_1 W_{ij} y_{i,t} + u_{i,t}, \quad (u_{it} = \theta W_u + \varepsilon), \tag{5}$$

where i: provincial index, t: year. W_u: spatial lag of errors; θ: indicates the spatial dependence between neighboring provinces of error terms. ε: vector (n×1) of errors, normally distributed, with mean 0 and standard deviation σ. W_{ij}: spatial weight matrix between two provinces i and j, calculated in the standardized spatial weight matrix W, with:

$$W = \begin{bmatrix} W_{11} & W_{12} & \dots & W_{1n} \\ W_{21} & W_{22} & \dots & W_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1} & W_{n2} & \dots & W_{nn} \end{bmatrix}, \tag{6}$$

and $$W_{ij}^{s} = \frac{W_{ij}}{\sum_j W_{ij}},$$

From the above general models, when combined with considering variables in the present study, they become:

$$\begin{aligned} GINI_{i,t} &= \alpha + \beta_1 \ln EDU\_EXP_{i,t} \\ &+ \beta_2 InsQlt_{i,t} + \beta_3 \ln EDU\_EXP_{i,t} \cdot InsQlt_{i,t} \\ &+ \sum \delta_j Control_{i,t} + \rho W \cdot GINI_{i,t} \\ &+ \varphi W \cdot \ln EDU\_EXP_{i,t} + u_{i,t}, \\ &(u_{it} = \theta W_u + \varepsilon), \end{aligned} \tag{7}$$

where *GINI* is income inequality; *InsQlt* is institution quality proxied by PCI and/or PAPI indices; *EDU_EXP* is public education spending; and φ is the effect of the exogenous impact of neighboring areas of explanatory variable $W \times EDU\_EXP_{i,t}$.

Based on the numerical simulations, LeSage and Pace (2009) show that the Spatial Durbin Model (SDM) yields unbiased estimates and often outperforms more restrictive specifications such as the SAR, SEM, SAC, and related spatial lag or error models. Accordingly, we adopt the SDM as our baseline specification. To capture interprovincial dependence, we construct two alternative spatial weight matrices: a contiguity-based matrix and an inverse-distance matrix.

Model selection is conducted by estimating SAR, SEM, SAC, and SDM specifications and comparing their Akaike Information Criterion (AIC) values, with preference given to the model minimizing the AIC. We also perform robust Lagrange Multiplier (LM) tests for SAR and SEM alternatives under the null hypothesis of no spatial dependence. Finally, a Hausman test is employed to determine whether fixed or random effects are more appropriate.

Regarding data sources, public education expenditure (*EDU_EXP*) is obtained from the Vietnam Statistical Yearbook and measured at the provincial level. It includes both recurrent and capital spending on education, training, and vocational education across public institutions such as vocational training centers, continuing education centers, colleges, and local secondary schools. This expenditure supports training programs, human capital development, professional activities, and education-related social policies.

Institutional quality is proxied by two complementary provincial indices: the Provincial Competitiveness Index (*PCI*) and the Provincial Governance and Public Administration Performance Index (PAPI). While *PCI* (VCCI – Vietnam Chamber of Commerce and Industry) captures the quality of provincial economic governance from the perspective of private firms, *PAPI* (VUSTA – Vietnam Union of Science and Technology Associations & UNDP – United Nations Development Programme) reflects public governance and service delivery from citizens' viewpoints, thereby jointly representing the economic and administrative dimensions of institutional quality in Vietnam. Using both indices allows for a more comprehensive assessment of institutional quality across provinces.

GINI is the main dependent variable. For 2018–2024, provincial GINI coefficients are taken from official statistics published by the National Statistics Office (NSO). For earlier years, comparable estimates are constructed from the Vietnam Household Living Standards Survey (VHLSS), following Nguyen et al. (2025), to ensure a consistent panel over 2011–2024 (The dataset is limited to 2024, as Vietnam's provincial administrative restructuring in 2025 affects data consistency and comparability. The dataset will be provided by the corresponding author upon reasonable request). To complement the GINI index, we additionally employ ICGAP and TOP20, which are constructed from provincial income distribution data provided by the NSO. These indicators capture distinct dimensions of inequality: GINI reflects overall income dispersion, ICGAP measures disparities across different segments of the distribution, and *TOP*20 captures the concentration of income among the top earners. Together, they allow for robustness checks across alternative measures of inequality.

In addition to the main explanatory variables, we include a set of socioeconomic and demographic controls – health expenditure, development investment, non-farm household income, literacy rate, and urban population – to capture broader provincial dynamics of poverty and inequality.

Health expenditure (*HLH_EXP*) reflects public investment in healthcare that enhances pro-

Table 1. Descriptive statistics

Source: Vietnam Statistical Yearbooks Database.

Variable	Obs	Mean	SD	P25	Median	P75
GINI	882	0.379	0.052	0.347	0.379	0.412
ICGAP	882	7.141	1.390	6.377	7.070	7.909
TOP20	882	0.448	0.041	0.423	0.443	0.473
EDU_EXP	882	3,126.937	2,407.817	1,881.000	2,594.500	3,540.000
HLH_EXP	882	828.915	604.469	481.000	680.500	950.000
INVEST	882	5,348.643	7,018.809	1,905.000	3,554.500	5,934.000
INC	882	6,543.937	2,283.589	4,781.000	6,219.500	7,915.000
LITERACY	882	93.458	6.569	92.600	95.300	97.700
URBAN	882	524.705	970.664	174.730	266.650	483.270
PCI	882	62.123	4.791	58.760	62.445	65.460
PAPI	882	39.621	3.907	36.184	39.580	43.070

Note: Expenditures (*_EXP), INVEST, and INC are millions of VND.

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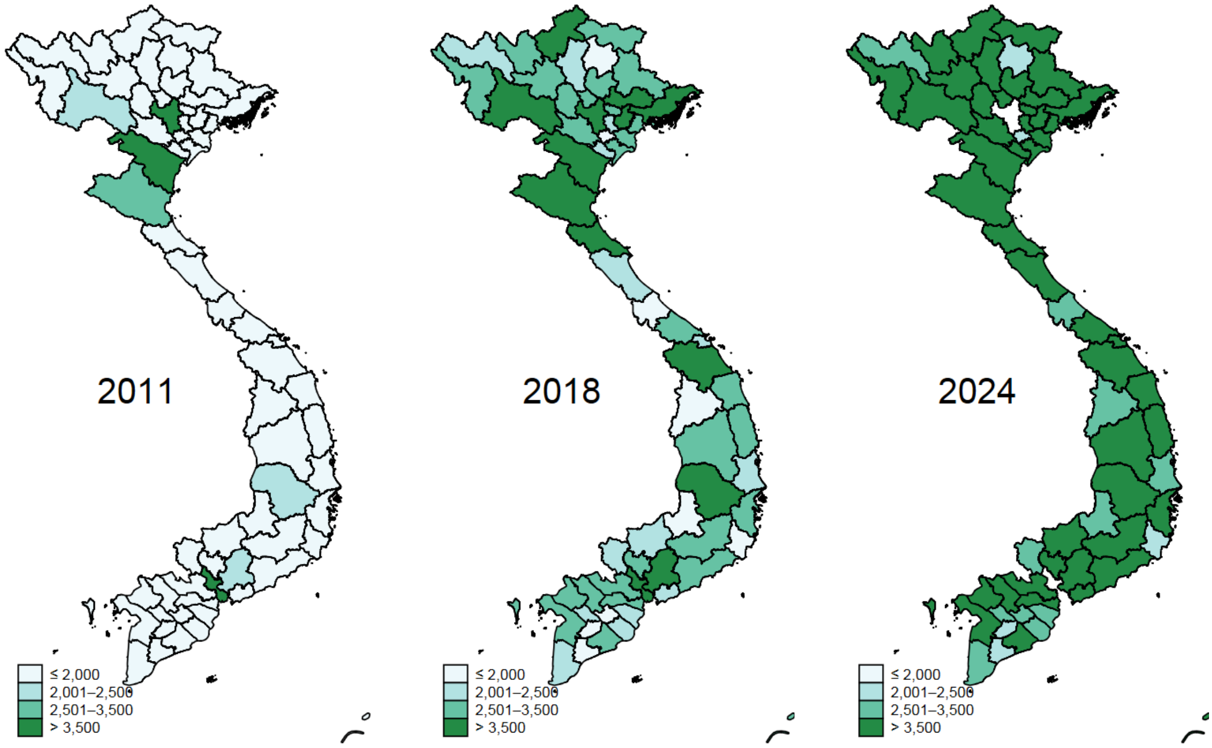


Note: The spatial distribution of public education expenditure across Vietnamese provinces in 2011, 2018, and 2024.

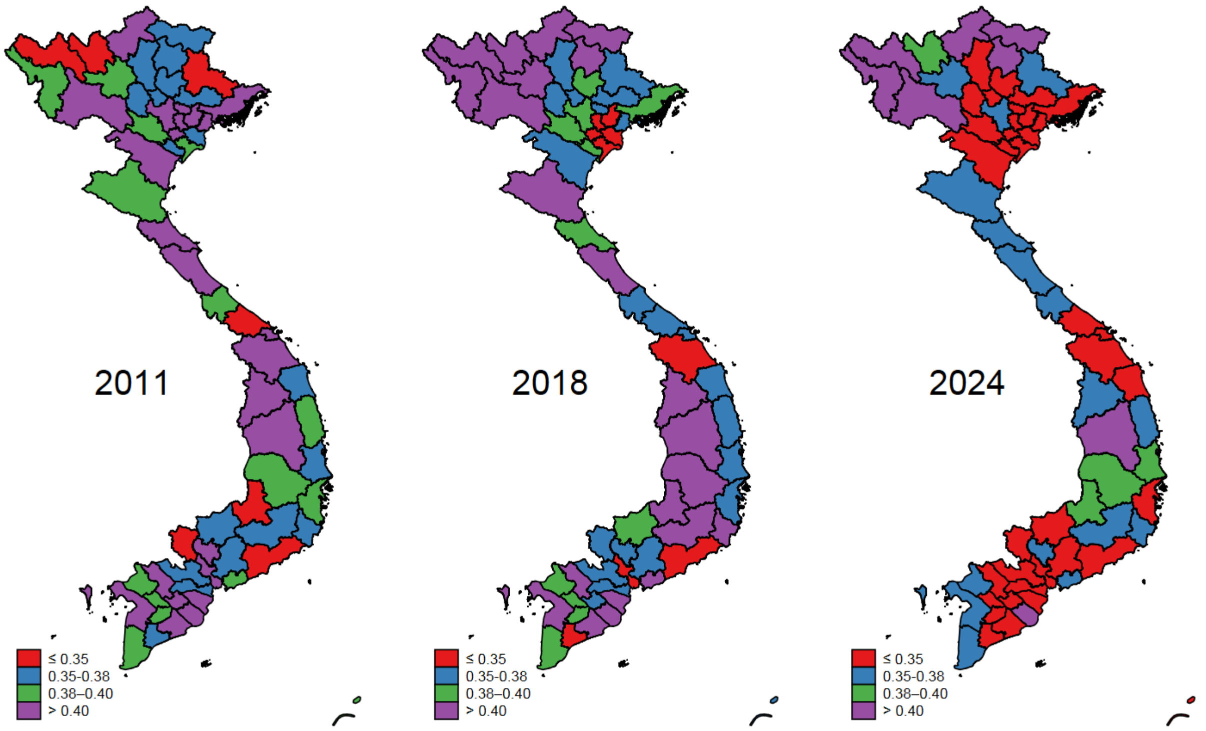
Figure 2. Vietnam's public education expenditure progress

ductivity and reduces vulnerability (O'Donnell, 2024). Development investment (*INVEST*) proxies for capital accumulation and economic growth (Ruch & Geyer Jr, 2017), while non-farm household income captures income diversification and labor market participation (Moyo et al., 2022). Literacy rate (*LITERACY*) measures human capital and earning potential (Collin & Weil, 2020), and urban population (*URBAN*) reflects structural transformation and spatial inequality (Liddle, 2017). All variables are sourced from the Vietnam Statistical Yearbook, with expenditure variables adjusted for provincial price indices. Table 1 presents descriptive statistics for 63 provinces over 2011–2024.

To illustrate the changes over time and space in public education spending in Vietnam, Figure 2 shows maps of provincial expenditures for 2011, 2018, and 2024. Provinces are categorized into four levels, ranging from low (light blue green) to high (dark green). Over time, the maps reveal a clear upward shift in spending intensity, with darker shades spreading nationwide – signifying Vietnam's sustained and broad-based commitment to education investment.

In contrast, Figure 3 illustrates the spatial distribution of income inequality (*GINI*) across provinces for the same years. While some provinces, such as Ha Giang, Gia Lai, Dak Nong, and Tra Vinh, consistently exhibit high inequality, others, including Hanoi, Da Nang, and Ho Chi Minh City, maintain lower levels. Regional disparities persist, with some provinces showing improvement and others worsening over time. These spatial patterns indicate that inequality reduction in Vietnam is neither uniform nor simultaneous across regions. They also suggest that institutional and policy factors, along with inter-provincial spillovers, may influence the observed disparities – issues further examined in the subsequent regression analysis to inform equitable development strategies.

The results of the spatial autocorrelation test using Moran's I (Table 2) indicate that income inequality exhibits strong and statistically significant positive spatial dependence across all distance thresholds examined (See also Figures B1-B3 in Appendix B) Specifically, the Global Moran's I equals 0.280 at 50 km, 0.163 at 100 km, and 0.101 at 150 km, with corresponding Z-scores of 24.92, 24.27, and 22.32 (all p-values = 0.000). These highly significant re-



Note: The map illustrates the spatial clustering of inequality (GINI index) over 2011, 2018, and 2024.

Figure 3. Vietnam's inequality progress (*GINI*)

sults confirm that provinces with similar levels of income inequality tend to be spatially clustered rather than randomly distributed. In other words, provinces with high inequality are more likely to be located near other high-inequality provinces, and similarly for low-inequality provinces. This provides clear evidence of spatial clustering in income inequality across Vietnam.

Table 2. Moran's I at different distance thresholds (Global)

Distances (Km)	I	EI	zI	pI
50	0.28068	−0.00113	24.919	0.000
100	0.16250	−0.00113	24.268	0.000
150	0.10540	−0.00113	22.319	0.000

Moreover, the Local Moran's I (LISA) statistics (Table 3) reveal clear evidence of spatial clustering in the distribution of income inequality across provinces. A substantial number of observations fall into High-High (245) and Low-Low (329) clusters, with a large proportion being statistically significant at the 1% level across all three distance thresholds. This indicates the existence of persistent "hotspots" (high-inequality provinces surrounded by high-inequality neighbors) and "coldspots" (low-inequality provinces surrounded by low-inequality neighbors). In contrast, the High-Low and Low-High clusters are less frequent, suggesting the presence of only a few spatial outliers – provinces whose inequality levels diverge substantially from those of their neighbors. Overall, the results strongly support the use of spatial econometric models to capture the spatial structure of inequality in Vietnam.

Model selection is performed by comparing the SAR, SEM, and SDM estimators using the Akaike Information Criterion (AIC) (Table A3 in Appendix A). A lower AIC indicates a better balance between model fit. Across all three inequality indicators (*GINI*, *ICGAP*, and *TOP*20), the SDM specification achieves the lowest AIC values – for instance, in the *GINI* regressions, the SDM reports an AIC of −3,504.06, outperforming both the SAR (−3,496.55) and SEM (−3,482.58) models. Consistent results are obtained for *ICGAP* and *TOP*20. Based on this criterion, the SDM is identified as the preferred spatial model. SAR or SEM also be seen as the robustness test for the SDM one.

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Table 3. Local Moran's I results

Summary of Local Moran's I (dist = 50 km)				
Spatial Cluster Type	**Obs**	**p10**	**p05**	**p01**
High-High	298	122	106	87
High-Low	148	41	39	30
Low-High	123	15	8	6
Low-Low	313	139	121	106
Summary of Local Moran's I (dist = 100 km)				
Spatial Cluster Type	**Obs**	**p10**	**p05**	**p01**
High-High	269	106	94	77
High-Low	177	67	56	49
Low-High	124	18	12	7
Low-Low	312	174	154	138
Summary of Local Moran's I (dist = 150 km)				
Spatial Cluster Type	**Obs**	**p10**	**p05**	**p01**
High-High	245	110	100	82
High-Low	201	92	87	71
Low-High	107	19	13	8
Low-Low	329	186	169	145

Note: See associated Figures B1-B3 in Appendix B.

We estimate the spatial panel models by maximum likelihood, using the Stata implementation developed by Belotti et al. (2017). Maximum likelihood estimation is well suited to the Spatial Durbin Model (SDM) because it allows the spatial lag of the dependent variable and the spatially lagged covariates to be estimated jointly within a single framework, thereby accounting explicitly for spatial dependence and the simultaneity induced by regional interactions. Under correct model specification, this approach yields consistent and asymptotically efficient estimates. By contrast, conventional OLS is generally inappropriate in this setting because it does not account for endogenous spatial interaction effects. To strengthen statistical inference, we report robust standard errors clustered by expenditure patterns (Harris & Guermat, 2000). This estimation strategy is also consistent with earlier empirical studies that rely on maximum likelihood to estimate SDM specifications and obtain robust results (Del Bo & Florio, 2012; Que et al., 2018; Yu et al., 2013).

3. RESULTS

Table 4 reports the baseline estimations from panel models examining the effect of public education expenditure (ln*EDU_EXP*) on income inequality (*GINI*) and the moderating role of institutional quality measured by *PCI* and *PAPI*. Across the fixed-effects models, ln(*EDU_EXP*) exhibits a positive and statistically significant coefficient, indicating that higher public spending on education is associated with higher income inequality. The estimated coefficient ranges from 0.098 to 0.237 across models (1–4), suggesting that increases in education expenditure are linked to increases in the *GINI* index. This result is consistent with the statement of hypothesis H1.

Likewise, *PCI* and *PAPI* are positive and significant in the corresponding models, indicating that improvements in institutional quality are correlated with higher measured inequality in the sample period. Importantly, the interaction variables (ln(*EDU_EXP*)×*PCI* and ln(*EDU_EXP*)×*PAPI*)) are negative and statistically significant across the fixed-effects models, confirming that stronger institutions mitigate the inequality-enhancing association of education spending. In particular, the interaction effects are estimated at around –0.004 in the PCI-based models and –0.003 in the PAPI-based models, implying that the marginal effect of education expenditure on inequality declines as governance quality improves. This result empirically supports hypothesis H2.

To further address potential endogeneity concerns, columns (5) and (6) of Table 4 present the System-GMM estimates. These dynamic models are formulated to mitigate bias arising from reverse causality, simultaneity, omitted time-varying shocks, and the inclusion of lagged inequality. The lagged *GINI* variable is large and highly significant (0.721 and 0.662), confirming strong persistence in income inequality over time. Even after accounting for these concerns, ln(*EDU_EXP*) remains positive and significant, while the interaction variables *PCI* and *PAPI* remain negative and significant. This indicates that the main baseline pattern is robust: public education expenditure is associated with higher income inequality, but stronger institutions attenuate this relationship.

Taken together, the baseline results indicate that public education expenditure is associated with higher income inequality, but this effect weakens as institutional quality improves. However, given spatial dependence, these estimates may be incomplete, as interactions likely extend across neighboring provinces. Therefore, the analysis next turns to spatial econometric models.

Model selection tests reported earlier indicate that the Spatial Durbin Model (SDM) is the most appropriate framework for assessing these spatial effects. In addition to *GINI* (SDM1 and SDM2), the using *ICGAP* (SDM3 and SDM4) and *TOP*20 (SDM5 and SDM6) to verify that the results are not driven by a single inequality proxy and to capture different distributional dimensions, namely overall inequality, income gaps across the distribution, and upper-tail concentration. Table 5 reports the SDM estimates using the contiguity weight matrix (Wc) for all three inequality measures.

The SDM estimates confirm the baseline findings. Across all models, ln(*EDU_EXP*) remains positive

Table 4. Baseline panel regressions

Variable | Model	Fixed Effects				System-GMM	
Dep. variable: *GINI*	(1)	(2)	(3)	(4)	(5)	(6)
GINI(-1)					0.721^{***}	0.662^{***}
					(0.010)	(0.017)
ln(*EDU_EXP*)	0.201^{**}	0.237^{***}	0.098^{*}	0.113^{*}	0.058^{***}	0.027^{**}
	(0.082)	(0.085)	(0.057)	(0.061)	(0.013)	(0.012)
PCI	0.026^{**}	0.027^{***}			0.005^{***}	
	(0.010)	(0.010)			(0.002)	
PAPI			0.021^{*}	0.019		0.000
			(0.011)	(0.012)		(0.002)
ln(*EDU_EXP*)×PCI	-0.004^{***}	-0.004^{***}			-0.001^{***}	
	(0.001)	(0.001)			(0.000)	
ln(*EDU_EXP*)×*PAPI*			-0.003^{**}	-0.003^{*}		−0.000
			(0.001)	(0.001)		(0.000)
ln(*HLH_EXP*)		−0.012		−0.007	-0.006^{***}	-0.008^{***}
		(0.008)		(0.008)	(0.001)	(0.002)
ln*INVEST*		-0.014^{**}		-0.013^{*}	−0.001	-0.002^{**}
		(0.007)		(0.007)	(0.001)	(0.001)
ln*INC*		−0.011		−0.006	0.004^{*}	0.000
		(0.023)		(0.022)	(0.002)	(0.001)
LITERACY		0.003^{**}		0.003^{*}	-0.001^{***}	-0.001^{***}
		(0.002)		(0.002)	(0.000)	(0.000)
ln*URBAN*		-0.045^{**}		-0.042^{*}	−0.000	-0.005^{***}
		(0.022)		(0.022)	(0.000)	(0.001)
Constant	−1.055	-1.175^{*}	−0.264	−0.270	−0.164	0.177^{**}
	(0.646)	(0.630)	(0.453)	(0.498)	(0.106)	(0.074)
Observations	882	882	882	882	819	819
Adjusted R^2	0.196	0.239	0.200	0.231		
AR(1), p-value					0.000	0.000
AR(2), p-value					0.513	0.641

Note: Clustered-robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01. "ln" denotes the logarithm operator.

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Table 5. Spatial Durbin Model (SDM) estimations

Variable | Model	SDM1	SDM2	SDM3	SDM4	SDM5	SDM6
Main						
ln(*EDU_EXP*)	0.141***	0.057*	4.129***	1.996***	0.120***	0.068***
	(0.027)	(0.030)	(1.039)	(0.701)	(0.022)	(0.012)
PCI	0.019***		0.557***		0.016***	
	(0.004)		(0.117)		(0.003)	
PAPI		0.014**		0.494***		0.015***
		(0.007)		(0.116)		(0.002)
ln(*EDU_EXP*)×PCI	−0.002***		−0.069***		−0.002***	
	(0.000)		(0.014)		(0.000)	
ln(*EDU_EXP*)×*PAPI*		−0.002**		−0.061***		−0.002***
		(0.001)		(0.015)		(0.000)
ln(*HLH_EXP*)	−0.006	−0.003	−0.290	−0.303*	−0.007	−0.007
	(0.006)	(0.007)	(0.180)	(0.180)	(0.005)	(0.005)
ln*INVEST*	−0.008***	−0.006**	−0.117**	−0.112**	−0.008***	−0.008***
	(0.003)	(0.003)	(0.053)	(0.047)	(0.002)	(0.002)
ln*INC*	−0.007	−0.003	−0.147	−0.009	−0.003	−0.001
	(0.016)	(0.015)	(0.223)	(0.208)	(0.007)	(0.007)
LITERACY	0.002***	0.002**	0.048**	0.048**	−0.000	−0.000
	(0.001)	(0.001)	(0.021)	(0.021)	(0.001)	(0.001)
ln*URBAN*	−0.041***	−0.038***	−0.052	0.064	0.012	0.016*
	(0.010)	(0.011)	(0.164)	(0.220)	(0.007)	(0.009)
Wc						
ln(*EDU_EXP*)	0.026*	0.029*	0.487***	0.493***	0.011*	0.013**
	(0.014)	(0.015)	(0.113)	(0.107)	(0.006)	(0.005)
Spatial						
ρ	0.487***	0.489***	0.655***	0.662***	0.525***	0.531***
	(0.053)	(0.052)	(0.050)	(0.046)	(0.029)	(0.030)
Observations	882	882	882	882	882	882
Number of groups	63	63	63	63	63	63
Log-likelihood	1759.74	1755.49	−891.41	−906.31	2189.10	2183.24
Hausman chi2	25.710***	27.970***	17.250*	18.060*	40.460***	37.840***

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "ln" denotes the logarithm operator.

and statistically significant (0.057–0.141 for *GINI*; 1.996–4.129 for *ICGAP*; 0.068–0.120 for *TOP*20), reinforcing the baseline conclusion that higher education expenditure increase inequality (As stated in hypothesis *H1*.) At the same time, the institutional quality indicators (*PCI* and *PAPI*) enter with positive and significant coefficients, whereas their interaction variables (ln(*EDU_EXP*)×PCI and ln(*EDU_EXP*)×*PAPI*) are negative and highly significant. This result reaffirms that the statement in hypothesis H2 is true. Appendix A (Tables A1 and A2) further confirms robustness across SAR-W_C and SDM-W_i specifications, with ln(*EDU_EXP*) remaining positive and significant, PCI/PAPI interactions remaining negative and significant.

Beyond confirming the baseline relationships, Table 5 also shows that spatial interaction is economically meaningful. The spatial lag of public education spending W_C×ln(*EDU_EXP*) is positive and significant for *GINI* and *ICGAP*, implying spillover effects from neighboring provinces' education spending on local inequality outcomes. By contrast, the corresponding coefficient is small and statistically insignificant for TOP20. In addition, the spatial autoregressive parameter ρ is strongly positive across all models, 0.487-0.662, confirming substantial spatial dependence in inequality outcomes. The Hausman test results also favor fixed effects, supporting the FE-SDM model.

These SDM coefficients indicate that inequality is shaped by both within-province factors and cross-provincial linkages. However, in spatial models, the estimated coefficients do not directly represent marginal effects because changes in one province can feed back through the spatial system. This necessitates breaking down the SDM estimates into direct, indirect, and total effects. Accordingly, Table 6 presents the SDM impact decomposition.

Table 6 shows that the direct effects of ln(*EDU_EXP*) are positive and statistically significant across all models, indicating that higher education expenditure within a province is associated with greater inequality in that province. Because ln(*EDU_EXP*) enters in logarithmic form while the inequality indicators are measured in levels, these coefficients are interpreted as semi-elasticities: a 1% increase in public education spending changes the relevant inequality measure by 0.01 times the reported coefficient. In the *GINI* models, the direct semi-elasticity ranges from 0.067 to 0.157, implying that a 1% increase in education spending raises own-province *GINI* by approximately 0.0007 to 0.0016 points. The indirect effects are likewise positive, highly significant, and generally larger than the direct effects. For *GINI*,

Table 6. Direct, indirect, and total marginal effects

Variable | Model	SDM1	SDM2	SDM3	SDM4	SDM5	SDM6
Direct						
ln(*EDU_EXP*)	0.157***	0.067**	4.998***	2.503***	0.135***	0.077***
	(0.030)	(0.034)	(1.082)	(0.764)	(0.025)	(0.013)
PCI	0.021***		0.657***		0.017***	
	(0.004)		(0.122)		(0.003)	
PAPI		0.015**		0.585***		0.017***
		(0.007)		(0.124)		(0.003)
ln(*EDU_EXP*)×PCI	−0.003***		−0.082***		−0.002***	
	(0.001)		(0.015)		(0.000)	
ln(*EDU_EXP*)×*PAPI*		−0.002**		−0.073***		−0.002***
		(0.001)		(0.017)		(0.000)
ln(*HLH_EXP*)	−0.006	−0.003	−0.333	−0.350*	−0.008	−0.007
	(0.007)	(0.008)	(0.206)	(0.207)	(0.005)	(0.005)
ln*INVEST*	−0.008***	−0.007**	−0.138**	−0.129**	−0.009***	−0.008***
	(0.003)	(0.003)	(0.061)	(0.055)	(0.002)	(0.003)
ln*INC*	−0.008	−0.005	−0.179	−0.014	−0.004	−0.001
	(0.017)	(0.016)	(0.246)	(0.228)	(0.007)	(0.007)
LITERACY	0.003***	0.002***	0.057**	0.058**	−0.000	−0.000
	(0.001)	(0.001)	(0.025)	(0.025)	(0.001)	(0.001)
ln*URBAN*	−0.044***	−0.042***	−0.053	0.100	0.013*	0.017*
	(0.010)	(0.011)	(0.192)	(0.267)	(0.007)	(0.009)
Indirect						
ln(*EDU_EXP*)	0.171***	0.102**	8.374***	4.833***	0.147***	0.096***
	(0.043)	(0.043)	(0.983)	(0.736)	(0.030)	(0.015)
PCI	0.017***		0.960***		0.016***	
	(0.004)		(0.119)		(0.004)	
PAPI		0.012**		0.874***		0.016***
		(0.006)		(0.093)		(0.003)
ln(*EDU_EXP*)×PCI	−0.002***		−0.120***		−0.002***	
	(0.001)		(0.013)		(0.000)	
ln(*EDU_EXP*)×*PAPI*		−0.002**		−0.108***		−0.002***
		(0.001)		(0.014)		(0.000)
ln(*HLH_EXP*)	−0.005	−0.002	−0.445*	−0.488*	−0.007	−0.006
	(0.006)	(0.007)	(0.246)	(0.255)	(0.004)	(0.005)
ln*INVEST*	−0.006***	−0.005***	−0.198**	−0.192**	−0.008***	−0.008***
	(0.002)	(0.002)	(0.081)	(0.078)	(0.002)	(0.002)
ln*INC*	−0.006	−0.004	−0.271	−0.021	−0.004	−0.001
	(0.014)	(0.014)	(0.387)	(0.366)	(0.007)	(0.007)
LITERACY	0.002***	0.002***	0.082**	0.086**	−0.000	−0.000
	(0.000)	(0.000)	(0.032)	(0.034)	(0.001)	(0.001)
ln*URBAN*	−0.036***	−0.034***	−0.100	0.133	0.012*	0.016*
	(0.008)	(0.011)	(0.310)	(0.426)	(0.007)	(0.008)

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Table 6 (cont.). Direct, indirect, and total marginal effects

Variable | Model	SDM1	SDM2	SDM3	SDM4	SDM5	SDM6
			Total			
ln(*EDU_EXP*)	0.328***	0.168**	13.372***	7.335***	0.281***	0.173***
	(0.068)	(0.074)	(1.670)	(1.382)	(0.053)	(0.025)
PCI	0.037***		1.617***		0.034***	
	(0.007)		(0.196)		(0.007)	
PAPI		0.028**		1.458***		0.033***
		(0.013)		(0.193)		(0.005)
ln(*EDU_EXP*)×PCI	–0.005***		–0.202***		–0.004***	
	(0.001)		(0.022)		(0.001)	
ln(*EDU_EXP*)×*PAPI*		–0.004**		–0.181***		–0.004***
		(0.002)		(0.028)		(0.001)
ln(*HLH_EXP*)	–0.011	–0.005	–0.778*	–0.838*	–0.015	–0.013
	(0.012)	(0.014)	(0.447)	(0.458)	(0.009)	(0.010)
ln*INVEST*	–0.014***	–0.012**	–0.336**	–0.321**	–0.017***	–0.016***
	(0.004)	(0.005)	(0.138)	(0.129)	(0.004)	(0.005)
ln*INC*	–0.014	–0.008	–0.450	–0.035	–0.008	–0.001
	(0.031)	(0.030)	(0.629)	(0.592)	(0.015)	(0.014)
LITERACY	0.005***	0.004***	0.139**	0.144**	–0.001	–0.001
	(0.001)	(0.001)	(0.055)	(0.057)	(0.001)	(0.001)
ln*URBAN*	–0.080***	–0.076***	–0.153	0.233	0.025*	0.034*
	(0.017)	(0.021)	(0.500)	(0.690)	(0.014)	(0.018)
Observations	756	756	756	756	756	756

Note: Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01. SDM denotes Spatial Durbin Models. "ln" denotes the logarithm operator.

they range from 0.102 to 0.171, indicating that a 1% increase in education spending in one province raises *GINI* in neighboring provinces by about 0.001 to 0.0017 points. This suggests that education expenditure influences inequality not only within provinces but also through spillover channels across provinces. When these local and cross-provincial channels are considered jointly, the total effects remain positive and statistically significant across all specifications. At the same time, the interaction terms involving *PCI* and *PAPI* remain negative and significant throughout, indicating that stronger institutional quality mitigates both the within-province and spillover effects of education expenditure on inequality.

Overall, the results reveal a consistent pattern across the baseline, spatial, and impact estimates: education spending is positively associated with income inequality, but this association weakens as institutional quality improves.

4. DISCUSSION

The results indicate that public education expenditure in Vietnam increases income inequality, and this effect is moderated by institutional quality, in the context of spatial spillovers across provinces. This finding suggests that education spending does not automatically translate into expected outcomes but instead interacts with governance conditions and regional dynamics. The results are consistent with evidence that the initial gains from education investment may accrue disproportionately to higher-income or more skilled groups when access is uneven (Artige & Cavenaile, 2023).

The findings of this study also suggest that the impact of public education spending depends on institutional quality and implementation efficiency. This interpretation is consistent with prior evidence, which shows that in contexts of weak governance, public resources are more likely to be subject to elite capture, inefficiencies, and poor targeting, thereby limiting their benefits for disadvantaged groups (Gupta et al., 2002; Rajkumar & Swaroop, 2008). In addition, our findings are consistent with Doumbia and Kinda (2019) as well as Kyriacou (2025), indicating that stronger institutions – particularly through enhanced transparency and accountability – can attenuate the inequality-increasing effects of public education expenditure. It further aligns with the "inverted-U" hypothesis of Voto and Ngepah (2024), whereby at low-to-medium spending levels, education outlays can raise inequality before becoming equalizing beyond a coverage or effectiveness threshold.

However, our findings contrast with earlier studies, which report a negative relationship between education spending and inequality (Gregorio & Lee, 2002; Sylwester, 2002). This contrast highlights how the effectiveness of education spending depends heavily on contextual factors, particularly the specific institutional and structural conditions found in Vietnam. Benefit-incidence analyses show that higher-level education spending is often regressive, benefiting better-off households, whereas primary education is more progressive (Cuong et al., 2010; Lam, 2017; World Bank, 2004). Moreover, persistent regional disparities in access – especially in remote and ethnic minority areas – limit the equalizing impact of education investment (Minot et al., 2006; UNDP, 2019; World Bank, 2022). As a result, increases in education spending may reinforce existing inequalities without effective targeting and governance.

In summary, these findings indicate that attaining equitable education spending requires more than simply increasing budget allocations; it also demands stronger institutional quality, more effective targeting mechanisms, and better coordination among provinces. Without such reforms, public education expenditure may continue to generate uneven distributional effects despite its intended role in narrowing inequality gaps.

CONCLUSION

This study explores how public education spending affects income inequality across Vietnamese provinces, specifically considering the mediating roles of institutional quality and spatial dependence. The results show that, on average, higher education expenditure correlates with increased income inequality, indicating that the benefits are unevenly shared among different groups. However, institutional quality significantly moderates this effect: better governance, transparency, and accountability help reduce the inequality caused by education spending. Additionally, the presence of notable spatial dependence suggests that both inequality and policy effects cross provincial boundaries, reflecting wider regional interactions and spillover effects.

These findings suggest that merely increasing education budgets is unlikely to achieve equitable outcomes. Instead, the effectiveness of policies heavily relies on institutional capacity, how allocation mechanisms are designed, and coordination across provinces. Therefore, strengthening governance, better targeting education spending toward disadvantaged groups, and improving interprovincial policy coordination are crucial to ensuring that education investment fosters inclusive growth.

Several avenues for future research emerge from this analysis. First, disaggregating education expenditure (such as distinguishing between primary and tertiary spending) could yield deeper insights into its distributional consequences. Second, the use of micro-level or household-level data would allow for a more detailed examination of the mechanisms through which education spending affects inequality. Finally, future studies could adopt dynamic identification strategies to better capture the long-term impacts of education investment and institutional change.

AUTHOR CONTRIBUTIONS

Conceptualization: Vo Van Hung.
Data curation: Vo Van Hung.
Formal analysis: Vo Van Hung.
Funding acquisition: Pham Thai Binh.
Methodology: Vo Van Hung, Pham Thai Binh.
Software: Vo Van Hung.

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Visualization: Vo Van Hung.
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Writing – review & editing: Vo Van Hung, Pham Thai Binh.

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APPENDIX A. Additional robustness checks

To assess the robustness of the baseline SDM results, we re-estimate the models using two alternative spatial models:

(i) a Spatial Autoregressive (SAR) model with the contiguity matrix *Wc*; and

(ii) an SDM with the inverse-distance matrix *Wi* (Tables A1 and A2).

Across the SAR models, ln(*EDU_EXP*) remains positive and statistically significant for *GINI*, *ICGAP*, and *TOP*20, and the interaction variables with PCI/PAPI remain negative and significant, confirming that institutional quality dampens the inequality-increasing association of education spending. The spatial autoregressive parameter ρ is also positive and highly significant, indicating strong spatial dependence.

The SDM estimates using inverse distance matrix closely mirror the baseline results: ln(*EDU_EXP*) remains positive and significant in most models, while the interaction variables with PCI/PAPI remain negative and significant. Notably, the spatial lag *Wi*×ln(*EDU_EXP*) is positive and highly significant across all SDM-*Wi* specifications, providing consistent evidence of spillovers from neighboring provinces' education spending. Overall, the SAR-*Wc* and SDM-*Wi* results confirm that the main conclusions are robust to alternative spatial models and weight matrices and further justify the use of spatial econometric methods for provincial inequality in Vietnam.

Table A1. Spatial autoregressive (SAR) estimations

Variable | Model	SAR1	SAR2	SAR3	SAR4	SAR5	SAR6
Main						
ln(*EDU_EXP*)	0.155***	0.072*	4.387***	2.260***	0.127***	0.075***
	(0.037)	(0.041)	(1.036)	(0.705)	(0.020)	(0.010)
PCI	0.019***		0.556***		0.016***	
	(0.004)		(0.117)		(0.003)	
PAPI		0.014*		0.493***		0.015***
		(0.007)		(0.114)		(0.002)
ln(*EDU_EXP*)×*PCI*	−0.002***		−0.069***		−0.002***	
	(0.001)		(0.014)		(0.000)	
ln(*EDU_EXP*)×*PAPI*		−0.002**		−0.061***		−0.002***
		(0.001)		(0.015)		(0.000)
ln(*HLH_EXP*)	−0.005	−0.002	−0.260	−0.274	−0.007	−0.006
	(0.007)	(0.008)	(0.182)	(0.180)	(0.005)	(0.005)
ln*INVEST*	−0.008**	−0.006**	−0.117**	−0.112***	−0.008***	−0.008***
	(0.003)	(0.003)	(0.049)	(0.042)	(0.002)	(0.002)
ln*INC*	0.001	0.006	0.003	0.144	0.000	0.003
	(0.014)	(0.013)	(0.231)	(0.211)	(0.007)	(0.007)
LITERACY	0.003***	0.002***	0.051**	0.052**	−0.000	−0.000
	(0.001)	(0.001)	(0.020)	(0.021)	(0.000)	(0.001)
ln*URBAN*	−0.039***	−0.036***	−0.009	0.107	0.013*	0.017*
	(0.010)	(0.011)	(0.159)	(0.214)	(0.007)	(0.009)
Spatial						
ρ	0.487***	0.490***	0.657***	0.664***	0.526***	0.532***
	(0.053)	(0.052)	(0.050)	(0.046)	(0.030)	(0.031)
Observations	882	882	882	882	882	882
Number of groups	63	63	63	63	63	63
Log-likelihood	1758.27	1753.69	−892.78	−907.67	2188.35	2182.26
Hausman chi2	20.270**	21.440**	18.350**	19.550**	39.460***	35.920***

Note: Spatial Autoregressive (SAR) Models with WC matrix. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. "ln" denotes the logarithm operator.

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Table A2. Spatial Durbin model (SDM) estimations with inverse distance matrix (Wi)

Variable | Model	SDM1	SDM2	SDM3	SDM4	SDM5	SDM6
Main						
ln(*EDU_EXP*)	0.130***	0.034	4.429***	1.795**	0.097***	0.042**
	(0.021)	(0.024)	(1.114)	(0.748)	(0.028)	(0.018)
PCI	0.020***		0.633***		0.015***	
	(0.003)		(0.141)		(0.003)	
PAPI		0.014**		0.529***		0.014***
		(0.006)		(0.147)		(0.003)
ln(*EDU_EXP*)×*PCI*	−0.003***		−0.080***		−0.002***	
	(0.000)		(0.018)		(0.000)	
ln(*EDU_EXP*)×*PAPI*		−0.002**		−0.066***		−0.002***
		(0.001)		(0.019)		(0.000)
ln(*HLH_EXP*)	−0.005	−0.005	−0.336*	−0.340*	−0.007	−0.006
	(0.007)	(0.007)	(0.179)	(0.184)	(0.005)	(0.005)
ln*INVEST*	−0.004	−0.003	−0.084*	−0.085*	−0.006***	−0.005**
	(0.003)	(0.003)	(0.048)	(0.046)	(0.002)	(0.002)
ln*INC*	−0.030*	−0.025	−0.484*	−0.372	−0.013	−0.011
	(0.018)	(0.018)	(0.284)	(0.283)	(0.009)	(0.009)
LITERACY	0.003***	0.003***	0.093***	0.092***	0.000	0.000
	(0.001)	(0.001)	(0.022)	(0.023)	(0.000)	(0.000)
ln*URBAN*	−0.029***	−0.027***	0.247*	0.348*	0.020***	0.023***
	(0.008)	(0.008)	(0.147)	(0.210)	(0.005)	(0.007)
$W_i \times X$						
ln(*EDU_EXP*)	0.059***	0.062***	1.094***	1.167***	0.038***	0.041***
	(0.017)	(0.020)	(0.312)	(0.372)	(0.006)	(0.007)
Spatial						
ρ	0.748***	0.750***	0.834***	0.838***	0.756***	0.759***
	(0.035)	(0.038)	(0.031)	(0.029)	(0.022)	(0.028)
Observations	882	882	882	882	882	882
Number of groups	63	63	63	63	63	63
Log-likelihood	1752.52	1742.35	−928.75	−946.49	2197.76	2190.11
Hausman chi2	28.730***	34.220***	23.490***	25.110***	39.870***	40.160***

Note: SDM denotes spatial Durbin model. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. "ln" denotes the logarithm operator.

Table A3. Selection of spatial models using AIC and robust LM tests

Models		SAR	SEM	SDM
		(1)	(2)	(3)
GINI	AIC	−3496.55	−3482.58	−3504.06
	LM test (robust)	23.58***	36.87***	
ICGAP	AIC	1805.57	1822.03	1787.94
	LM test (robust)	33.71***	48.42***	
*TOP*20	AIC	−4356.69	−4346.82	−4371.99
	LM test (robust)	31.46***	39.59***	

Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Models are estimated using the contiguity-based weighting matrix (Wc). SAR, SEM and SDM are spatial autoregresive model, spatial error model and spatial Durbin model, respectively.

APPENDIX B. Moran's I scatterplot for GINI

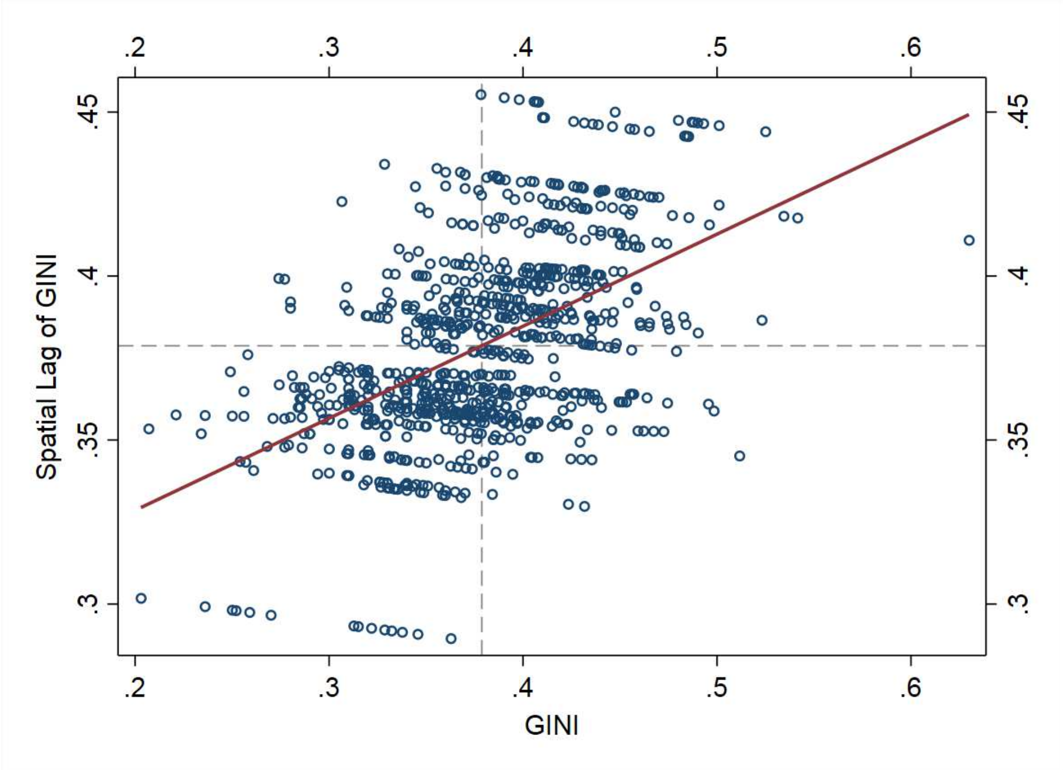

Figure B1. Moran's I scatterplot for GINI (50 km)

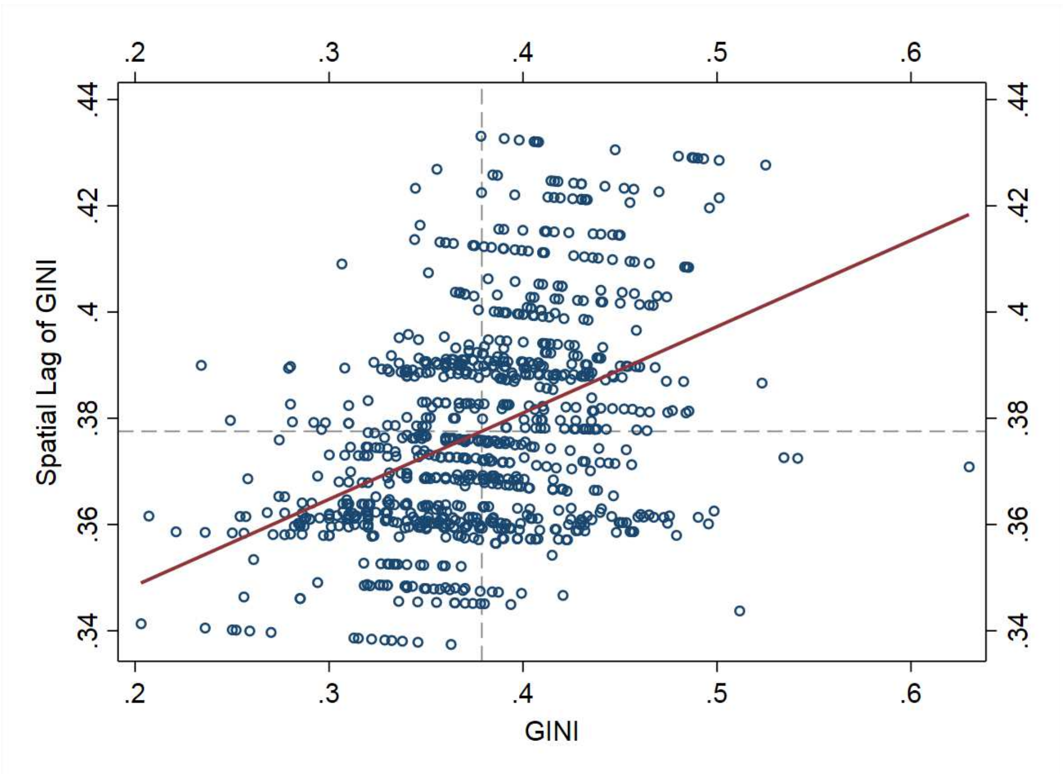

Figure B2. Moran's I scatterplot for GINI (100 km)

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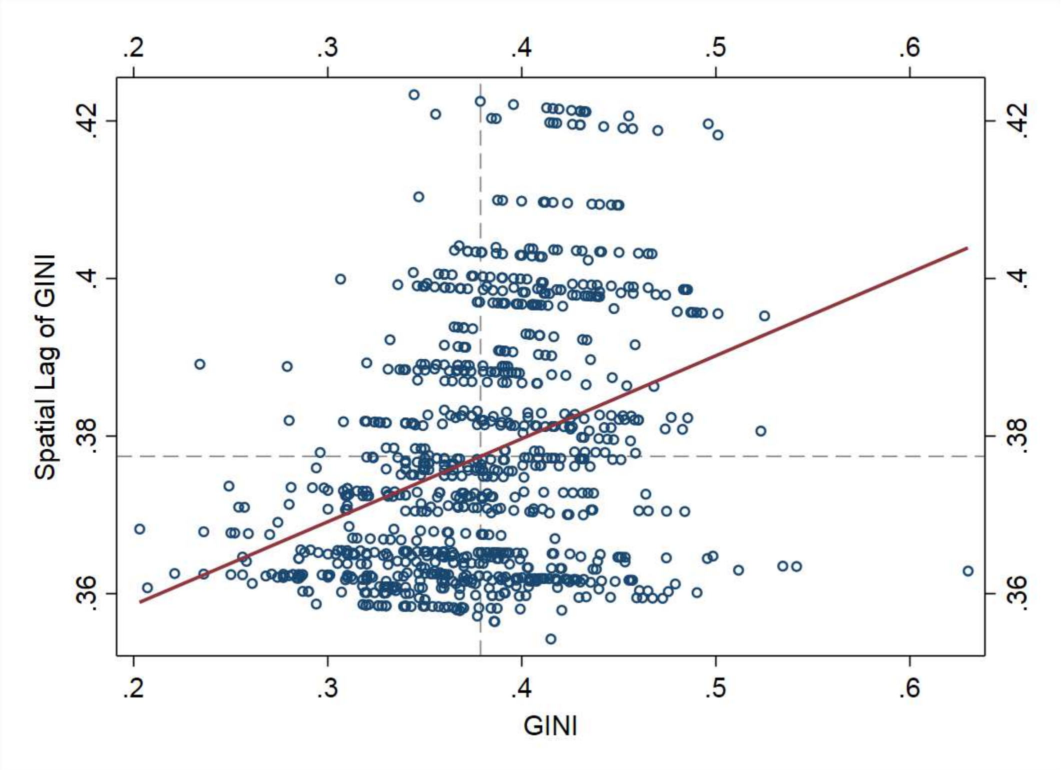

Figure B3. Moran's I scatterplot for GINI (150 km)