International Journal of Sustainable Development and Planning
Vol. 21, No. 3, March, 2026, pp. 1123-1137
Journal homepage: http://iieta.org/journals/ijsdp

Income Inequality and Carbon Intensity: The Role of Inclusive Financial Development

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https://doi.org/10.18280/ijsdp.210314

Received: 10 January 2026
Revised: 5 March 2026
Accepted: 15 March 2026
Available online: 31 March 2026

Keywords:
income inequality, carbon intensity, financial development, inclusive finance

ABSTRACT

This study addresses the dual challenge of income inequality and environmental degradation in emerging Asian economies, where rapid growth often exacerbates both issues. While previous research has examined the direct impacts of inequality or finance on emissions, a significant gap exists in understanding their interactive dynamics. This paper fills this gap by arguing that inclusive finance is not merely an explanatory variable but a crucial moderator that reshapes the inequality-emissions nexus. Employing a panel dataset for 22 Asian nations from 2000 to 2022, the study utilizes a two-step System Generalized Method of Moments (GMM) estimator to address endogeneity and persistence. A mean-centered interaction term is introduced to test the moderating hypothesis, and a threshold analysis based on marginal effects is conducted to identify the point at which this moderation becomes effective. The empirical results robustly confirm that income inequality significantly increases carbon intensity ($\beta = 0.011$, $p < 0.05$). Critically, the study provides strong evidence for the negative moderating role of financial development (FD), as indicated by the significant negative coefficient of the interaction term ($\beta = -0.098$, $p < 0.05$). This signifies that a more inclusive financial system weakens the adverse environmental impact of inequality. Further analysis identifies a key policy threshold for the financial development index ($FD \approx 0.509$), beyond which the harmful effect of inequality is neutralized. These findings offer a significant contribution by reframing the policy debate from a trade-off to a synergy. The study concludes that promoting inclusive FD is not only a social objective but also a strategic instrument for mitigating environmental pressures, enabling a development path that is simultaneously more equitable and sustainable.

1. INTRODUCTION

In the context of globalization, humanity faces an unprecedented challenge in simultaneously addressing two urgent goals of the United Nations' 2030 Agenda: Reducing inequality (Goal 10) and Climate Action (Goal 13). Although economic growth has lifted millions out of poverty, its benefits have not been distributed evenly, leading to a widening wealth gap while pushing the global ecosystem to its limits due to soaring CO_2 emissions [1]. The complex relationship between income inequality and environmental degradation has become a subject of intense debate in development economics, yet empirical evidence remains mixed and lacks a consistent consensus [2, 3].

This context is particularly severe in emerging Asian economies. The region is currently considered the world's growth engine, but it is also the largest emitter of greenhouse gases and has recorded the fastest increase in income inequality [4, 5]. The convergence of three factors—rapid growth, deep wealth polarization, and severe environmental pollution—in Asia has posed a formidable challenge for policymaking. The core issue is whether efforts to narrow the income gap inadvertently increase pressure on the environment by boosting energy consumption, or vice versa.

Previous studies have approached this issue from two separate strands. One focuses on the Environmental Kuznets Curve (EKC) hypothesis, testing the singular impact of income or inequality on emissions [6-8]. The other examines the role of financial development (FD) in environmental quality, yielding conflicting conclusions on whether finance promotes green technology or dirty energy consumption [9, 10]. These approaches share two critical limitations. First, they treat inequality and finance as independent predictors, neglecting their potential interactive dynamics. Second, the frequent reliance on inconsistent inequality data from the World Development Indicators (WDI), which contains many missing observations for developing countries, has undermined the reliability and comparability of previous estimates.

This neglect of the interactive mechanism constitutes a significant gap, particularly in the Asian context. Most existing research has inadvertently overlooked a crucial reality: the financial system is not merely a channel for capital allocation but can also function as a social instrument that regulates the energy consumption behavior of different income strata. Specifically, the degree to which inequality translates into environmental pressure may be contingent upon the inclusiveness of the financial system. To address this gap, the present study poses two specific research questions: (RQ1) Does income inequality significantly increase carbon intensity in emerging Asian economies? (RQ2) Does inclusive FD act as a negative moderator that weakens the positive relationship between income inequality and carbon intensity, and if so, what is the threshold of FD at which the harmful effect of inequality is neutralized?

To answer these questions, this study departs from the conventional approach of treating finance solely as an explanatory variable and instead frames it as a moderating mechanism. The research employs data from the Standardized World Income Inequality Database (SWIID) by Solt [11] to overcome the data limitations of previous studies, combined with the International Monetary Fund's (IMF's) multidimensional FD index [12]. By applying System Generalized Method of Moments (GMM) and Driscoll-Kraay estimation methods to handle endogeneity and cross-sectional dependence, the study provides new empirical evidence on the "green" moderating role of inclusive finance in mitigating the dual challenge of inequality and emissions.

Beyond the introduction, the remainder of the paper is structured as follows: Section 2 provides a theoretical overview and hypothesis development. Section 3 describes the data and research methodology. Section 4 presents the empirical results. Section 5 discusses the research findings. Finally, Section 6 offers conclusions and important policy implications.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

2.1 Foundational theory

The theoretical framework of this study is built upon the integration of the political economy theory of the Environment and Financial Intermediation Theory, aiming to explain the complex interactive mechanism among income distribution, the financial system, and environmental quality.

First, from the political economy perspective of Boyce [13], income inequality negatively affects environmental quality through power asymmetry. High-income groups often benefit from polluting production activities and use their political power to obstruct environmental protection regulations, while low-income groups bear the ecological consequences but lack the voice to change policy. Additionally, Heerink et al. [14] add a demand-side perspective through the marginal propensity to emit hypothesis. In developing countries, high inequality limits the poor's access to clean and efficient energy sources, forcing them to overexploit natural resources or use cheap but high-emission biomass fuels to sustain their livelihoods.

However, the relationship between inequality and the environment does not operate in isolation but is governed by economic institutions, particularly the financial system. FD theory suggests that an efficient financial system can reduce information and transaction costs, thereby optimizing resource allocation [15]. Extending this to the dimension of inclusive finance, Sadorsky [16] and Le et al. [17] argue that relaxing credit constraints allows households and small businesses to access green technology and more efficient energy.

The intersection of these two theoretical streams forms the basis for the study's moderating hypothesis: Inclusive finance acts as a mechanism to correct market failures caused by inequality. As the financial system becomes more developed, it provides the necessary resources for low-income groups to move up the energy ladder, reducing their dependence on obsolete technology. Therefore, inclusive FD is expected to reduce carbon intensity and neutralize the negative impact of income inequality on the environment.

2.2 Development of research hypotheses

2.2.1 Income inequality and carbon intensity

The relationship between income inequality and environmental degradation, specifically carbon intensity, can be explained through two main transmission channels: political economy and consumption behavior.

First, from a political economy perspective, rising inequality exacerbates power asymmetry between social classes. According to the classic argument by Boyce [13], high-income groups typically hold greater political power and tend to favor policies that prioritize short-term economic growth over environmental protection. As the wealth gap widens, elites can use their influence to lobby for lower environmental standards or prevent the implementation of carbon taxes, leading to energy-intensive industries continuing to operate inefficiently [18]. Consequently, the economy consumes more energy to produce a unit of Gross Domestic Product (GDP), increasing carbon intensity.

Second, in terms of consumption behavior, inequality stimulates what is known as the Veblen effect or conspicuous consumption. In a deeply polarized society, individuals tend to increase their consumption of luxury and energy-intensive goods (such as large cars, spacious homes, and electronic devices) not for practical needs but to assert social status [6, 19]. This consumption race wastefully increases total energy demand. Simultaneously, at the bottom of the income ladder, relative poverty prevents households from accessing energy-saving technologies or clean fuels. Heerink et al. [14] point out that the poor are forced to overexploit natural resources or use outdated, low-efficiency equipment to maintain their livelihoods. The combination of wasteful consumption by the rich and low energy efficiency of the poor leads to an overall increase in the economy's emission intensity.

Empirically, recent studies have provided consistent evidence supporting the theoretical arguments above. Grunewald et al. [2] and Zhang and Zhao [20] confirm a positive relationship between the income gap and CO_2 emissions, especially in developing economies where environmental institutions are still weak. Delving into the impact mechanism, Yameogo and Dauda [21] and Yang et al. [22] argue that excessive wealth concentration undermines public governance effectiveness and financial stability, thereby neutralizing efforts to implement sustainable policies.

Furthermore, the complex link between rapid growth, inequality, and emission pressures requires integrated approaches to simultaneously address distributional and environmental problems [23-25]. Based on these theoretical and empirical foundations, we propose the first hypothesis:

H1. *Income inequality has a positive (+) effect, increasing carbon intensity.*

2.2.2 The moderating role of inclusive financial development

Although income inequality tends to increase carbon intensity, as argued in H1, we contend that this impact is not fixed but depends on the level of financial system development. Based on the theory of financial system functions, inclusive FD can mitigate the negative environmental consequences arising from uneven income distribution through three main impact mechanisms: relaxing credit constraints, promoting technological innovation, and optimizing energy efficiency.

First, inclusive finance helps break the vicious cycle of poverty and pollution by relaxing credit constraints for low-income populations. In economies with high inequality, the poor are often excluded from the formal financial system, forcing them to use cheap but high-emission biomass fuels like firewood or coal for their daily needs [14]. As inclusive finance expands, access to credit and payment services allows these households to afford a transition to cleaner energy sources or purchase energy-efficient appliances [16]. Thus, even if the income gap persists, better financial access helps reduce the marginal emission intensity of low-income groups [25].

Second, from a production perspective, inclusive FD enables small and medium-sized enterprises (SMEs) to access capital for investment in green technology. In developing countries, income inequality is often accompanied by inequality in access to business opportunities, where capital is concentrated in large corporations or old resource-extraction industries. Tamazian et al. [26] and Shahbaz et al. [27] argue that a developed financial system reduces the cost of capital and encourages firms to adopt more environmentally friendly production processes. The democratization of capital access helps alleviate the resource allocation inefficiencies caused by inequality, thereby reducing the energy intensity per unit of output.

Third, recent empirical evidence has begun to reinforce this moderating view. Le et al. [17], in their study of the Asian region, showed that inclusive finance has a significant emission-reducing effect and can offset the negative impacts of rapid growth. More importantly, Kakeu and Agbo [28] and Gardezi et al. [29] have provided direct evidence that FD acts as a negative moderator, weakening the positive relationship between income inequality and CO_2 emissions. Specifically, in countries with highly developed inclusive financial systems, the pollution-increasing effect of income inequality is significantly lower than in countries with weak financial systems. Renzhi and Baek [30] and Asongu and Odhiambo [31] also concur that inclusive finance helps mitigate the adverse impact of social inequality on environmental quality by promoting investment in sustainable projects.

In summary, we argue that inclusive finance not only directly affects the environment but also changes the nature of the relationship between inequality and carbon intensity. An inclusive financial system provides the necessary tools for economic agents to overcome income barriers and move towards greener consumption and production behaviors. Therefore, the second hypothesis is proposed as follows:

H2. *Inclusive FD plays a negative (-) moderating role, reducing the adverse impact of income inequality on carbon intensity.*

3. RESEARCH METHODOLOGY

3.1 Sample and data collection

To ensure the representativeness and reliability of the estimates, the study focuses on emerging and developing economies in Asia. The choice of this region is based on the fact that it is the world's fastest-growing area, but also one that is witnessing a simultaneous increase in both inequality and environmental pressure [4].

The research period spans 23 years, from 2000 to 2022. The selection of this timeframe is justified by three main reasons: (i) The year 2000 marks the recovery from the Asian financial crisis and the beginning of the Millennium Development Goals (MDGs), creating a structural shift in the data; (ii) This period covers major global economic fluctuations, including the 2008 financial crisis and the COVID-19 pandemic, allowing for testing the model's robustness to external shocks; (iii) This is the period with the best data coverage for the IMF's specialized financial indices.

The sample screening process was conducted as follows: from an initial list of Asian countries, we excluded: (i) Developed economies (such as Japan, South Korea, Singapore) due to their distinct saturated economic and technological structures; (ii) Countries with more than 20% missing data in the observed time series (e.g., North Korea, Afghanistan). The final sample consists of 22 emerging and developing countries in Asia, forming a relatively balanced panel dataset with a total of 506 country-year observations.

Data sources were compiled from three reputable organizations: the World Bank's WDI for macroeconomic and environmental variables (Accessed at: databank.worldbank.org); SWIID (Accessed at: fsolt.org/swiid) for the GINI variable; and the International Monetary Fund (IMF) (Accessed at: data.imf.org) for the FD index. To mitigate the influence of outliers that could distort regression results, all continuous variables in the model were treated with winsorization at the 1st and 99th percentiles.

3.2 Research model

Based on the analyzed theoretical foundation and EKC hypothesis, we construct a basic log-linear regression model.

In constructing a regression model containing a moderating variable, a common technical challenge is high multicollinearity. This problem arises because the interaction term (created by multiplying X × M) is often highly statistically correlated with its constituent individual variables (X and M). This interdependence can inflate the variance of the estimated coefficients, leading to inaccurate hypothesis testing.

To rigorously address this issue and ensure the model's robustness, the study applies the "Mean-Centering" technique. Specifically, before performing the multiplication to create the interaction term, we subtract the sample mean of the inequality and FD variables from their respective observed values. This data processing procedure adheres to the methodological recommendations of Aiken and West [32], significantly reducing multicollinearity between the interaction term and the independent variables, and also making the interpretation of the regression coefficients clearer.

The general regression equation is established as follows:

$$ln(CO_2)_{it} = \beta_0 + \beta_1 INEQ\_c_{it} + \beta_2 FD\_c_{it} + \beta_3(INEQ\_c_{it} \times FD\_c_{it}) + \beta_4 lnGDP_{it} + \beta_5 lnGDP^2_{it} + \beta_6 TO_{it} + \beta_7 URB_{it} + \beta_8 FDI_{it} + \mu_i + \varepsilon_{it}$$

where,

- i and t represent country and year, respectively.
- $ln(CO_2)_{it}$: Natural logarithm of Carbon Intensity.
- $INEQ\_c_{it}$: Gini coefficient from SWIID (mean-centered).
- FD_c_{it}: FD index from IMF (mean-centered).
- $(INEQ\_c_{it} \times FD\_c_{it})$: Interaction term representing the moderating role.
- Control variables include: lnGDP (Per capita income), $lnGDP^2$ (Squared income), TO (Trade openness), URB (Urbanization), FDI (Foreign direct investment).
- μ_i is the country-specific fixed effect, and ε_{it} is the random error term.

If hypothesis H2 is correct, we expect the coefficient β_3 to be negative (-), implying that as FD increases, the marginal effect of inequality on carbon intensity decreases.

3.3 Measurement of variables

The measurement of key variables was conducted based on a careful consideration of both foundational theory and data availability in developing countries.

Dependent Variable: Carbon Intensity

Instead of using total greenhouse gas emissions, this study uses Carbon Intensity (the ratio of CO_2 emissions to GDP, measured in kg per 2017 Purchasing Power Parity (PPP) $). The rationale for this choice stems from the context of developing Asian countries: during a period of rapid growth, demanding an absolute reduction in total emissions is unrealistic and could hinder poverty reduction goals. Therefore, "green growth" is understood as reducing the carbon usage required to generate one unit of economic output. Data is extracted from WDI and transformed into natural logarithm form to normalize the distribution and interpret coefficients as elasticities.

Main Independent Variable: Income Inequality

We use the GINI coefficient of disposable income (after taxes and transfers) from Solt's [11] SWIID version 9.1 dataset. Although WDI also provides a GINI coefficient, this data for developing countries is often intermittent and lacks consistency in survey methodology across years. SWIID overcomes this limitation by using an imputation algorithm to maximize comparability across countries and over time, and is considered the "gold standard" in international comparative research on inequality.

Moderating Variable: Inclusive Financial Development

Instead of using traditional single-metric measures like Private Credit/GDP (which often only reflects financial depth), this study uses the composite FD Index developed by Svirydzenka [12] for the IMF. This index is a multidimensional measure, encompassing three aspects: Depth, Access, and Efficiency of both financial markets and financial institutions. The use of this composite index is particularly suitable for the research objective on "inclusive finance," as it captures the access to financial services by the broader population, not just the scale of loans to large corporations.

Several data processing decisions were made to ensure the statistical validity of the estimates. First, carbon intensity and GDP per capita were transformed into natural logarithm form. This transformation serves two purposes: (i) it normalizes the right-skewed distribution that is typical of macroeconomic data, thereby reducing the influence of extreme values and satisfying the normality assumption for regression residuals; and (ii) it allows the estimated coefficients to be directly interpreted as elasticities, which is more intuitive for policy analysis. Second, all continuous variables were winsorized at the 1st and 99th percentiles. In the context of a heterogeneous sample of 22 countries spanning 23 years, extreme outliers—often caused by data recording errors or one-off economic shocks—can disproportionately influence ordinary least squares (OLS)-based estimates. Winsorization truncates these extreme values to the boundary percentiles, preserving sample size while limiting the leverage of outliers on the regression line. Together, these processing steps enhance the robustness and reliability of the subsequent estimations. The variables in the research model are detailed in Table 1 below.

Table 1. Definition and measurement of variables

Variable Name	Symbol	Definition and Measurement	Source	Expected Sign
		Dependent Variable		
Carbon Intensity	$ln(CO_2)_{it}$	Natural logarithm of CO_2 emissions per unit of GDP (kg/USD at 2017 PPP).	WDI	N/A
		Independent & Moderating		
Income Inequality	$Gini_{it}$	Gini coefficient of disposable income (scale 0–100).	SWIID	(+)
Financial Development	FD_{it}	Composite index of financial depth, access, and efficiency (scale 0–1).	IMF	(-)
Interaction Term	Gini_c × FD_c	Interaction between mean-centered Gini and FD to mitigate multicollinearity.	Calculated	(-)
		Control Variables		
Economic Development	$ln(GDP)_{it}$	Natural logarithm of GDP per capita (PPP 2017). Reflects the level of economic development.	WDI	(+)
Squared Economic Dev.	$ln(GDP)^2_{it}$	Square of $ln(GDP)_{it}$. Used to test the Environmental Kuznets Curve (EKC) hypothesis.	Calculated	(-)
Trade Openness	TO_{it}	Total trade (exports + imports) as a percentage of GDP (%).	WDI	±

Urbanization	Urb_{it}	Urban population as a percentage of total population (%).	WDI	(+)
Foreign Direct Investment	FDI_{it}	Net inflows of Foreign Direct Investment as a percentage of GDP (%).	WDI	±

Source: Synthesis of the author group

Note: WDI = World Development Indicators; SWIID = Standardized World Income Inequality Database; IMF = International Monetary Fund; PPP = Purchasing Power Parity.

3.4 Analysis method

The estimation strategy is implemented in a sequential and diagnostic-driven manner, progressing from baseline models to advanced techniques that address specific econometric concerns.

Step 1: Baseline model selection. Preliminary tests are conducted to determine the optimal static panel structure. The F-test is used to compare the Pooled OLS model against the Fixed Effects Model (FEM), and the Hausman test is subsequently applied to choose between FEM and the Random Effects Model (REM). These tests establish whether country-specific unobserved heterogeneity (such as energy culture, geography, or institutional quality) significantly influences the dependent variable.

Step 2: Controlling for cross-sectional dependence. In a globalized and regionally integrated sample of Asian economies, common shocks (e.g., oil price fluctuations, financial crises) can induce error correlation across countries. If present, conventional FEM standard errors become biased, leading to unreliable inference. The Pesaran CD [33] test is applied to the FEM residuals to diagnose this issue. If cross-sectional dependence is detected, the study re-estimates the model using the Driscoll-Kraay standard error procedure [34]. This method was chosen over alternatives (e.g., Panel-Corrected Standard Errors, or Newey-West) because it produces standard errors that are robust simultaneously to heteroskedasticity, serial autocorrelation, and cross-sectional dependence, making it particularly suitable for macro panels with moderate T and small N.

Step 3: Addressing endogeneity with System GMM. While the Driscoll-Kraay model addresses inference issues, it does not resolve potential endogeneity arising from reverse causality (e.g., high emissions may constrain economic growth, which in turn affects inequality) or omitted variable bias. Furthermore, carbon intensity exhibits strong temporal persistence, necessitating a dynamic specification. To address these issues, the study employs the two-step System GMM estimator developed by Arellano and Bover [35] and Blundell and Bond [36]. System GMM was preferred over Difference GMM because the latter suffers from weak instrument problems when the dependent variable is highly persistent—a condition confirmed by the lagged coefficient of approximately 0.84 in the results.

The System GMM estimator exploits two sets of moment conditions. For the first-differenced equation, lagged levels of the endogenous variables (Gini_c, FD_c, and their interaction term) dated t-2 and deeper are used as instruments, based on the assumption that past levels are correlated with current changes but uncorrelated with the differenced error term. For the levels equation, lagged first differences dated t-1 are used as instruments under the stationarity assumption. The strictly exogenous control variables (TO, URB, FDI) enter as standard IV-style instruments in both equations. To avoid the instrument proliferation problem, which can overfit the endogenous variables and weaken the Hansen test, the instrument count is restricted to 19 by collapsing the instrument matrix. The validity of this design is verified through the Arellano-Bond AR (2) test (confirming no second-order autocorrelation in the errors) and the Hansen J-test (confirming instrument exogeneity).

Step 4: Robustness checks. The robustness of the core findings is assessed through three approaches: (i) replacing the Gini coefficient with the Palma Ratio as an alternative inequality measure; (ii) sub-sample analysis by income group (lower-middle income (LMI) vs. upper-middle income (UMI)); and (iii) including the squared term of financial development (FD^2) to control for potential non-linearity that could bias the interaction term. All analyses were performed using Stata 17.

4. RESEARCH RESULTS

4.1 Descriptive statistics and correlation analysis

The objective of this section is to provide an overview of the distributional characteristics of the sample data, while also verifying the technical effectiveness of the mean-centering method in addressing multicollinearity, thereby establishing a solid foundation for the regression models in the subsequent sections.

Table 2 presents the descriptive statistics for the variables used in the model for 22 Asian countries during the 2000–2022 period.

Table 2. Descriptive statistics of variables

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
ln(CO_2)	Log of Carbon Intensity	506	-0.421	0.385	-1.892	0.654
Gini	Income Inequality	506	39.42	5.18	28.30	54.70
FD	Financial Development	506	0.384	0.172	0.095	0.781
ln(GDP)	Log of GDP per capita	506	8.654	1.023	6.412	10.850
TO	Trade Openness (%)	506	78.56	35.41	18.25	210.40
URB	Urbanization (%)	506	46.32	16.85	14.20	82.15
FDI	Foreign Direct Investment (%)	506	3.85	3.12	-2.45	18.60

Source: Authors' calculation using Stata software

Table 3. Correlation matrix and variance inflation factor (VIF)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	VIF
(1) $\ln(CO_2)$	1.000								-
(2) Gini_c	0.312*	1.000							1.45
(3) FD_c	-0.285*	-0.142	1.000						2.18
(4) Gini_c × FD_c	-0.115*	0.084	-0.065	1.000					**1.12**
(5) ln(GDP)	0.154	-0.185	0.642*	-0.021	1.000				3.65
(6) $\ln(GDP)^2$	0.112	-0.168	0.615*	-0.018	0.965*	1.000			3.58
(7) TO	0.045	-0.032	0.215*	0.012	0.324*	0.310*	1.000		1.32
(8) URB	0.185*	0.124	0.582*	-0.045	0.715*	0.695*	0.154	1.000	2.84
Mean VIF									**2.30**

Source: Authors' calculation using Stata software

Note: * denotes statistical significance at the 5% level. Gini_c and FD_c represent mean-centered variables used to generate the interaction term.

The statistics reveal a diversity in development levels and social structures across the Asian region. Notably, the Gini variable has a mean of 39.42 but a considerable range (from 28.30 to 54.70). This reflects a deep heterogeneity: while some countries have managed income distribution well, many other economies face a stark wealth gap. Similarly, FD index has a standard deviation of 0.172 with a wide range from a very low 0.095 to a level approaching that of developed countries at 0.781. The strong dispersion of these two key variables provides a crucial practical basis, justifying the need to study the interactive mechanism between them, as different levels of FD can lead to very different moderating effects on the relationship between inequality and the environment.

To preliminarily assess the linear relationships between variables and detect potential multicollinearity issues, the study uses a Pearson correlation matrix combined with the Variance Inflation Factor (VIF). The results are presented in Table 3.

The results from the correlation matrix show that the Gini_c variable has a significant positive correlation with $\ln(CO_2)$ ($r = 0.312$), providing initial support for hypothesis H1 regarding the negative impact of inequality on the environment. Conversely, the interaction term (Gini_c × FD_c) shows a negative correlation with carbon intensity ($r = -0.115$), suggesting a shock-absorbing moderating role for inclusive finance.

A key technical highlight in Table 3 is the multicollinearity test result. Typically, including an interaction term in a model would cause severe multicollinearity because the product term ($X \times M$) is highly correlated with its constituent variables. However, thanks to the application of the Mean-Centering technique as described in the methodology section, the VIF for the interaction term (Gini_c × FD_c) is only 1.12, which is very low compared to the warning threshold of 10. Concurrently, the mean VIF for the entire model is 2.30. This provides robust statistical evidence that multicollinearity has been thoroughly controlled. The independent variables and the interaction term are informationally distinct, ensuring that the estimated regression coefficients in the following sections are accurate and reliable.

Beyond its technical function of reducing multicollinearity, the mean-centering procedure has an important implication for the substantive interpretation of the regression coefficients. In a model with an interaction term, the coefficient of an individual variable (e.g., β_1 for Gini_c) represents the conditional effect of that variable when the other interacting variable is at zero. Without mean-centering, this "zero point" for the FD index (which ranges from 0.095 to 0.781) would be substantively meaningless, as no country in the sample has an FD score of zero. By subtracting the sample mean, the zero point of FD_c now corresponds to the average level of FD in the sample (FD = 0.384). Consequently, the coefficient β_1 can be directly interpreted as the effect of a one-unit increase in inequality on carbon intensity for a country with an average level of FD—a scenario that is empirically meaningful and policy-relevant. Similarly, β_2 (for FD_c) captures the effect of FD at the average level of inequality. This interpretive clarity is a key advantage of the mean-centering approach beyond its role in reducing VIF, as it ensures that the main effect coefficients reported in the regression tables correspond to substantively interpretable conditions within the sample.

4.2 Baseline estimation results and control for cross-sectional dependence

4.2.1 Model selection tests

Before delving into the analysis of regression coefficients, we perform standard tests to determine the optimal model structure. The F-test result shows a statistic of $F(21, 476) = 34.52$ ($p < 0.01$), rejecting the null hypothesis that the intercepts are homogeneous across countries, thereby confirming that FEM is more appropriate than the Pooled OLS model. This is entirely consistent with the reality that each Asian country possesses unique unobservable characteristics (such as energy consumption culture, geographical location) that influence its emission intensity.

Next, the Hausman test was conducted to compare FEM and REM. The result indicates a Chi-square (8) value of 42.15 ($p < 0.001$), rejecting the null hypothesis that the random errors are uncorrelated with the explanatory variables. Therefore, the FEM is selected as the baseline model, ensuring the consistency of the estimates by controlling for heterogeneity across countries.

4.2.2 Diagnosis of cross-sectional dependence

In the context of globalization and deep regional integration in Asia, economic shocks (such as financial crises or oil price fluctuations) often have spillover effects across countries, leading to cross-sectional dependence among units in the panel data. If this phenomenon is ignored, the estimated standard errors will be biased, leading to unreliable statistical tests [34].

To verify this, we use the CD test Pesaran [33] on the residuals of the FEM model. The result shows a CD statistic of 28.45 ($p < 0.000$), strongly rejecting the hypothesis of cross-sectional independence. This result confirms the existence of a strong spatial linkage among the economies in the sample. Therefore, using the standard errors of the conventional FEM is inappropriate. To address this, the study switches to using the Driscoll-Kraay standard error estimation method, which allows for robust estimates even in the presence of serial autocorrelation, heteroskedasticity, and cross-sectional dependence.

4.2.3 Regression results with Driscoll-Kraay standard errors

Table 4 presents the official regression results. To clarify the moderating role, we conduct the estimation in two steps: Column (1) is the direct effect model without the interaction term, and Column (2) is the full model including the interaction term between inequality and FD.

The estimation results from the Driscoll-Kraay model in Column (2) provide crucial empirical evidence to test the research hypotheses:

First, the coefficient of the Income Inequality variable (Gini_c) is positive and statistically significant at the 5% level ($\beta = 0.014$). This implies that, ceteris paribus, an increase in the income gap exacerbates the economy's carbon emission intensity. This result strongly supports hypothesis H1, reflecting the reality in developing Asian countries: wealth polarization leads to wasteful consumption behavior among the upper class and dependence on obsolete, energy-inefficient technology among the lower-income class.

Second, and most importantly, the coefficient of the interaction term (Gini_c × FD_c) is negative and statistically significant ($\beta = -0.112$, $p < 0.05$). This result confirms hypothesis H2, demonstrating the moderating role of inclusive FD. The negative sign of the interaction term indicates that the marginal effect of inequality on carbon intensity decreases as the level of FD increases. In other words, an inclusive and efficient financial system acts as a "shock absorber," helping to neutralize the negative environmental impacts of inequality by providing green capital and clean technology to disadvantaged groups.

Third, regarding the control variables, the results reinforce the Environmental Kuznets Curve (EKC) hypothesis. The coefficient of ln(GDP) is positive (1.142) while the coefficient of $\ln(GDP)^2$ is negative (-0.064), both highly statistically significant ($p < 0.01$). This confirms an inverted U-shaped relationship between income and carbon intensity in Asia: pollution increases in the early stages of growth but gradually decreases after the economy reaches a certain development threshold. Additionally, the urbanization process (URB) is also found to be a factor that increases emission intensity, reflecting the pressure of urban infrastructure expansion on energy demand in the region.

Table 4. Regression results of the impact of income inequality and financial inclusion on carbon intensity

Variables	(1) FE (Robust)	(2) Driscoll-Kraay
Key Independent Variables		
Gini_c (Inequality)	0.014***	0.014**
	(3.85)	(2.42)
FD_c (Financial Dev.)	-0.185***	-0.185***
	(-4.12)	(-3.56)
Interaction Term		
Gini_c × FD_c		**-0.112****
		(-2.15)
Control Variables		
ln(GDP)	1.125***	1.142***
	(5.62)	(4.85)
$\ln(GDP)^2$	-0.062***	-0.064***
	(-5.15)	(-4.32)
TO (Trade Openness)	0.001	0.001
	(1.45)	(1.12)
URB (Urbanization)	0.004**	0.004*
	(2.35)	(1.89)
FDI	-0.008*	-0.008
	(-1.78)	(-1.54)
Constant	-4.521***	-4.685***
	(-4.25)	(-3.92)
Model Statistics		
Observations	506	506
Number of Groups	22	22
R-squared (within)	0.542	0.568
F-test (Prob > F)	0.000	0.000
Pesaran CD test	28.45***	-

Source: Authors' calculation using Stata software

Notes: t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is the natural logarithm of Carbon Intensity ($\ln CO_2$). Model (1) uses Fixed Effects with robust standard errors. Model (2) employs Driscoll-Kraay standard errors to control for cross-sectional dependence, autocorrelation, and heteroskedasticity.

4.3 Addressing endogeneity: Results from the System Generalized Method of Moments model

Although the Driscoll-Kraay estimation method has effectively controlled for cross-sectional dependence and autocorrelation, static models may still suffer from potential endogeneity issues. In the context of emerging Asian economies, reverse causality can occur when environmental degradation negatively impacts economic growth or exacerbates social inequality. Furthermore, CO_2 emissions often exhibit high persistence over time; specifically, the emission level of the previous period strongly influences the current period due to the rigidity of infrastructure and technology, which are difficult to change in the short term.

To rigorously address these issues and ensure the robustness of the conclusions, the study employs the two-step System GMM model. The estimation results are presented in Table 5, placed alongside the Driscoll-Kraay results for convenient comparison.

The results from the System GMM model in Column (2) show a high degree of similarity in sign and statistical significance compared to the Driscoll-Kraay model, affirming the consistency and reliability of the research hypotheses.

First, the coefficient of the lagged variable L.ln(CO_2) is positive and highly statistically significant at the 1% level (β = 0.842). This value indicates a strong persistence of carbon emissions in Asian countries. Specifically, the current year's emission level is 84.2% influenced by the previous year's level. This reflects the reality that the green transition in developing economies faces many barriers due to dependence on old energy infrastructure that is difficult to change in the short run.

Table 5. System GMM estimation results and robustness comparison

Variables	(1) Driscoll-Kraay	(2) System GMM (2-step)
Lagged Dependent Variable		
L.ln(CO_2)	-	**0.842*****
		(0.045)
Key Independent Variables		
Gini_c (Inequality)	0.014**	**0.011****
	(2.42)	(2.15)
FD_c (Financial Dev.)	-0.185***	**-0.145*****
	(-3.56)	(-3.12)
Interaction Term		
Gini_c × FD_c	-0.112**	**-0.098****
	(-2.15)	(-2.04)
Control Variables		
ln(GDP)	1.142***	0.625**
	(4.85)	(2.38)
ln(GDP)^2	-0.064***	-0.038**
	(-4.32)	(-2.18)
TO (Trade Openness)	0.001	0.002
	(1.12)	(0.85)
URB (Urbanization)	0.004*	0.003
	(1.89)	(1.42)
FDI	-0.008	-0.005
	(-1.54)	(-0.92)
Constant	-4.685***	-2.150**
	(-3.92)	(-2.45)
Model Statistics		
Observations	506	484
Number of Groups	22	22
Number of Instruments	-	19
Diagnostic Tests		
Arellano-Bond AR(1) (p-value)	-	0.002
Arellano-Bond AR(2) (p-value)	-	0.345
Hansen J test (p-value)	-	0.412

Source: Authors' calculation using Stata software

Notes: Figures in parentheses report t-statistics for column (1) and z-statistics for column (2). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. L.ln(CO_2) represents the first-order lag of the dependent variable. Variables Gini and FD are mean-centered to mitigate multicollinearity.

Second, after controlling for dynamic effects and endogeneity, the coefficient of Income Inequality (Gini_c) remains positive and statistically significant (β = 0.011, $p < 0.05$). Although the magnitude of the coefficient has slightly decreased compared to the static model (as the lagged variable has explained part of the variation), this result reaffirms Hypothesis H1: Income inequality is a driving force for increasing carbon intensity. Wealth polarization continues to exert pressure on the environment through mechanisms of inefficient consumption and obstruction of consensus on environmental policy.

Third, and most importantly, the coefficient of the interaction term (Gini_c × FD_c) continues to maintain a negative sign and statistical significance (β = -0.098, $p < 0.05$). This is robust empirical evidence supporting Hypothesis H2. This result indicates that, even when considering complex endogenous factors, inclusive FD still acts as an effective shock-absorbing moderating mechanism. In countries with deeply developed financial systems, the negative environmental impact of inequality is significantly weakened. The financial system acts as a crucial channel for capital, helping low-income groups and small businesses overcome financial barriers to access cleaner energy solutions, thereby neutralizing the harmful effects of uneven income distribution.

To ensure the validity of the GMM estimates, we perform standard diagnostic tests. The results at the bottom of Table 5 show:

Arellano-Bond test: The test for first-order autocorrelation (AR1) has a p-value = 0.002 (< 0.05), rejecting the null hypothesis, indicating the presence of first-order autocorrelation (which is normal and expected in a dynamic model). More importantly, the test for second-order autocorrelation (AR2) has a p-value = 0.345 (> 0.10), accepting the null hypothesis that there is no autocorrelation in the errors at the second order. This confirms the model is correctly specified.

Hansen J-test: The p-value of 0.412 is in the safe zone (greater than 0.10 and less than 1.00), indicating that we cannot reject the null hypothesis of the validity of the instruments. This confirms that the instruments used are exogenous and the model does not suffer from over-identification.

4.4 Marginal effects analysis

Although the statistically significant negative coefficient of the interaction term in the regression models has confirmed the moderating role of inclusive finance, relying solely on the sign of the coefficient is insufficient to fully understand the dynamic nature of this relationship. To address the crucial policy question, "To what extent must the financial system develop to neutralize or reverse the negative environmental impact of inequality?", this section conducts an analysis of the marginal effect of income inequality on carbon intensity at different levels of FD.

Based on the baseline regression equation, the marginal effect of income inequality (Gini) on carbon intensity ($lnCO_2$) is not a constant but a function dependent on the level of FD. Using the partial derivative method according to Brambor et al. [37], the marginal effect is determined as follows:

$$\partial \ln(CO_2)/\partial Gini = \beta_1 + \beta_3 \times (FD - Mean\_FD)$$

where,

$\beta_1 = 0.014$: The direct effect coefficient of inequality (from the Driscoll-Kraay model).

$\beta_3 = -0.112$: The coefficient of the interaction term.

Mean_FD = 0.384: The mean value of the FD index in the research sample.

This equation shows that as the FD index (FD) increases, the marginal effect of inequality will gradually decrease (due to β_3 being negative).

To visualize this result, Figure 1 below illustrates the change in the marginal effect of inequality on carbon intensity across different levels of FD, accompanied by a 95% Confidence Interval (CI).

The analysis of the marginal effect of inequality on carbon intensity, as illustrated in Figure 1, reveals three key statistical characteristics:

First, the existence of a threshold point: The marginal effect line intersects the horizontal axis at a FD index level of FD ≈ 0.509. This is a critical turning point. In the region to the left of this threshold (FD < 0.509), the marginal effect of inequality is positive, and the lower bound of the 95% confidence interval is above zero. This confirms that in countries with less developed or lower-middle financial systems (like most observations in the sample), income inequality does indeed increase carbon intensity. In the region to the right of the threshold (FD > 0.509), the marginal effect turns negative. However, it should be noted that the 95% confidence interval in this region begins to include zero, indicating that the emission-reducing effect is not yet statistically strong at very high FD levels, but the reversal trend is clear.

Second, in the region to the left of the threshold (FD < 0.509), the marginal effect of inequality is positive and statistically significant at the 95% level, as the entire confidence interval lies above the zero line.

Third, in the region to the right of the threshold (FD > 0.509), the marginal effect of inequality turns negative. However, the 95% confidence interval in this region widens and includes zero, indicating that this effect is not statistically significant. Overall, the marginal effect line shows a clear downward slope as the FD index increases.

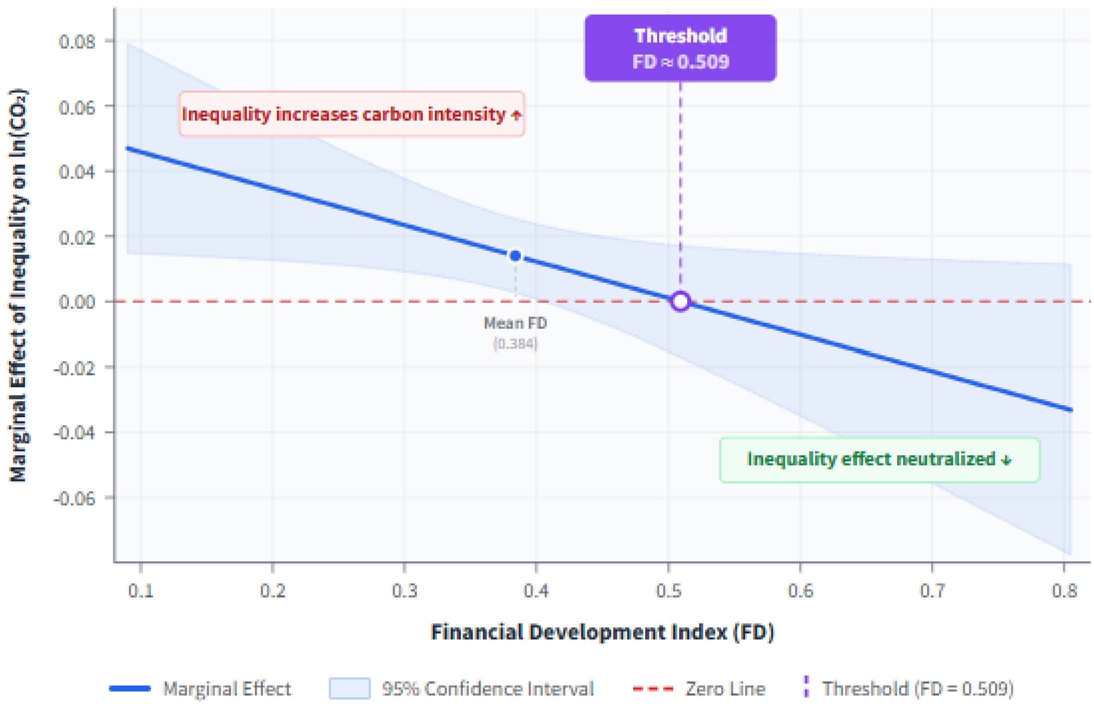

Figure 1. Marginal effect of income inequality on carbon intensity

Source: Authors' calculation based on Driscoll-Kraay regression results (Table 4, Column 2)

4.5 Robustness checks

4.5.1 Changing the independent variable measure: An approach from the Palmar Ratio

To test the model's robustness to different measures of income distribution, this study replaces the Gini coefficient with the Palma Ratio. Although the Gini coefficient is the most common measure, it is often criticized for being overly sensitive to changes in the middle of the income distribution while not clearly reflecting fluctuations at the extremes. In the context of environmental research, this can be a limitation, as political economy theory suggests that it is the wealthiest group (Top 10%) with their luxury consumption behavior and the poorest group (Bottom 40%) with their obsolete livelihood technologies that are the key actors exerting pressure on the ecosystem.

Therefore, we reconstruct the independent variable based on data from the World Bank's WDI, calculated as the ratio of the income share of the richest 10% to the income share of the poorest 40%. Using the Palma Ratio allows the model to more accurately capture the impact of extreme rich-poor polarization on carbon intensity. The re-estimated results using the System GMM method are presented in Column (1) of Table 6.

The results show remarkable consistency with the original model. The coefficient of the Palma Ratio is positive and statistically significant ($\beta = 0.182$, $p < 0.05$), confirming that the concentration of income in the wealthiest group increases carbon intensity. More importantly, the interaction term (Palma_c × FD_c) still maintains a negative sign and statistical significance ($\beta = -0.145$, $p < 0.05$). This reinforces the conclusion that FD helps mitigate the environmental damage caused by extreme wealth disparity, regardless of the inequality measure used.

4.5.2 Sub-sample analysis by income group

Asia is a region of great diversity in development levels. To examine heterogeneity in the impact mechanism, we divide the research sample into two groups based on the World Bank's classification: LMI group and UMI group. The results are presented in Columns (2) and (3), respectively.

The comparison between the two groups reveals interesting nuances in the Asian context:

(i) In the group of lower-middle-income countries (Column 2): The impact of inequality on carbon intensity is significantly stronger ($\beta = 0.019$) compared to the upper-middle-income group. This reflects the reality that in poorer countries, inequality is often linked to the poor being forced to use biomass fuels and obsolete technology for survival. Correspondingly, the moderating role of finance here is also very strong ($\beta = -0.135$), indicating that relaxing credit constraints has a large marginal impact in helping households and small businesses transition to cleaner energy.

Table 6. Robustness check results

Variables	(1) Alternative Measure (Palma Ratio)	(2) Lower-Middle Income (LMI)	(3) Upper-Middle Income (UMI)
Lagged Dependent Variable			
L.ln(CO_2)	0.815***	0.792***	0.865***
	(0.052)	(0.068)	(0.041)
Key Independent Variables			
Inequality [a]	0.182**	0.019**	0.009*
	(2.14)	(2.35)	(1.72)
Financial Development (FD_c)	-0.210***	-0.165**	-0.112**
	(-2.85)	(-2.41)	(-2.08)
Interaction Terms			
Inequality_c × FD_c [b]	-0.145**	-0.135**	-0.084**
	(-2.28)	(-2.10)	(-1.98)
Control Variables			
ln(GDP)	0.584**	0.712***	0.425*
	(2.05)	(2.95)	(1.68)
ln(GDP)^2	-0.035**	-0.045***	-0.024*
	(-1.98)	(-2.78)	(-1.65)
TO (Trade Openness)	0.002	0.003*	0.001
	(0.95)	(1.75)	(0.62)
URB (Urbanization)	0.004	0.005*	0.002
	(1.52)	(1.82)	(0.94)
FDI	-0.006	-0.009	-0.004
	(-1.15)	(-1.25)	(-0.75)
Constant	-1.950**	-2.845**	-1.420*
	(-2.10)	(-2.55)	(-1.85)
Model Statistics			
Observations	484	242	242
Number of Countries	22	11	11
Number of Instruments	19	17	17
Diagnostic Tests (p-value)			
AR(1)	0.004	0.008	0.012
AR(2)	0.315	0.285	0.410
Hansen J test	0.452	0.512	0.385

Source: Authors' calculations using Stata software

Notes: Figures in parentheses are z-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. [a] In Column (1), the Inequality variable is the Palma Ratio (sourced from SWIID data). In Columns (2) and (3), the Inequality variable is the Gini Coefficient as in the original model. [b] The interaction term is calculated based on the corresponding Inequality variable of each column and the mean-centered FD variable. Income groups are classified based on World Bank data at the start of the study period.

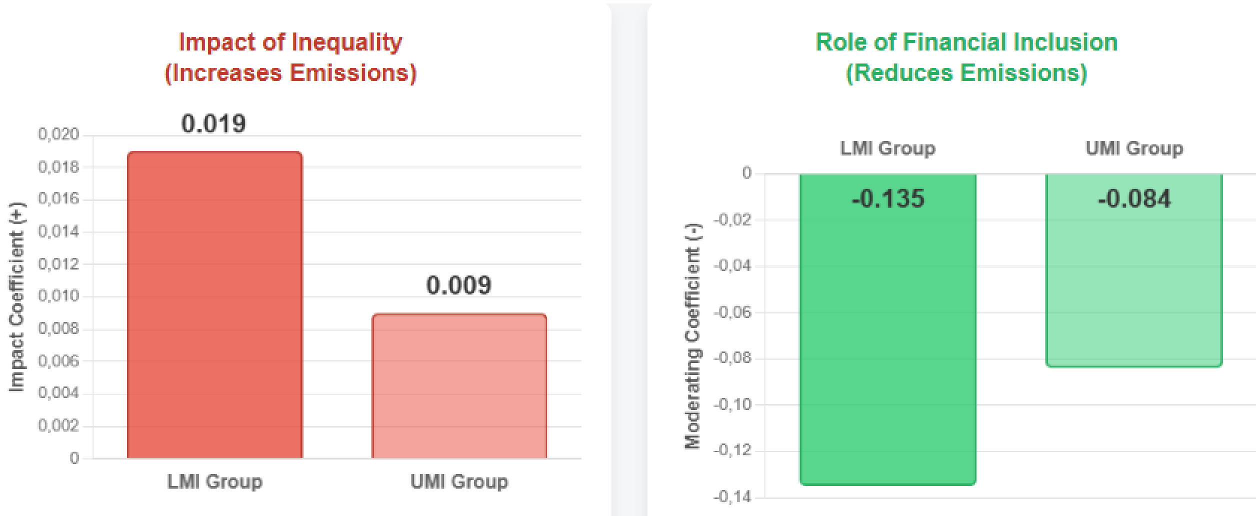

Figure 2. Environmental impact analysis coefficients comparison between asian country groups

Source: Authors' calculation based on regression results

Table 7. Robustness check results: Controlling for financial non-linearity

Variables	Coeff.	z-stat	P-value
Lagged dependent variable			
L.ln(CO_2)	0.835***	18.42	0.000
Main independent variables			
Gini_c (Inequality)	0.012**	2.18	0.029
FD_c (Financial Dev.)	-0.192***	-3.45	0.001
FD_c² (Squared FD)	0.085***	2.64	0.008
Interaction variable			
Gini_c × FD_c	-0.092**	-2.01	0.044
Control variables			
ln(GDP)	0.610**	2.25	0.024
ln(GDP)²	-0.035**	-2.08	0.038
TO (Trade Openness)	0.002	0.92	0.358
URB (Urbanization)	0.003	1.35	0.177
FDI	-0.006	-1.05	0.294
Constant	-2.085**	-2.32	0.020
Model statistics			
Observations	484		
Number of groups	22		
AR(2) test (p-value)	0.328		
Hansen J test (p-value)	0.445		

Source: Authors' calculations using Stata software

Note: ***, *, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The FD variable was mean-centered before squaring.

(ii) In the group of upper-middle-income countries (Column 3): Although the inequality coefficient decreases (β = 0.009) and its significance level is lower, it remains positive. Notably, the moderating role of finance still maintains statistical significance (β = -0.084). This implies that even when the economy is more developed, ensuring an inclusive financial system remains a key factor in curbing pollution-causing conspicuous consumption and promoting investment in advanced green technology.

Thus, the results from Table 6 show that the research hypotheses are robust and are not altered by different measurement methods or sub-sample characteristics, affirming the universality of the moderating role that the financial system provides

To visualize the differences in the impact mechanism between Asian country groups, Figure 2 compares the magnitude of the estimated regression coefficients for the inequality variable and the financial interaction term between LMI and UMI groups.

The results show that income inequality exerts a significantly stronger pressure to increase emissions in LMI countries (coefficient 0.019) compared to the UMI group (0.009). Concurrently, the moderating role of FD in mitigating this negative impact is also more effective in the LMI group (coefficient -0.135 versus -0.084), implying that lower-middle-income countries are more sensitive to both the pressure from inequality and the benefits from financial reform in the environmental context.

4.5.3 Controlling for the non-linearity of financial development

A common methodological concern in interaction models is the possibility that the interaction term (Gini_c × FD_c) might simply be a proxy for an omitted non-linear relationship of the moderator itself. Specifically, economic theory suggests that the impact of FD on the environment may not be entirely linear but could follow a law of diminishing returns or a U-shape. If a quadratic relationship (FD^2) actually exists but is omitted from the regression equation, this variation could be incorrectly absorbed by the interaction term, leading to biased conclusions about the moderating role.

To verify the robustness of hypothesis H2 and rule out the possibility of bias due to model misspecification, we extend the System GMM equation by adding the squared term of financial development (FD_c^2). The estimation results are detailed in Table 7.

The empirical results from Table 7 provide two important findings that accurately reflect the context of emerging economies:

First, the coefficient of the quadratic term FD_c^2 is positive and statistically significant ($\beta = 0.085$, $p < 0.01$). When combined with the negative coefficient of the linear term FD_c (-0.192), this indicates that the relationship between FD and carbon intensity in Asia has a U-shape (or diminishing returns). That is, finance helps reduce emissions strongly in the early stages of development, but the rate of environmental improvement slows down as the financial system reaches a higher saturation threshold. This is consistent with the reality that initial green investments often yield immediate results, but deeper technological improvements require a larger marginal cost.

Second, and most importantly, even after controlling for this non-linearity, the coefficient of the interaction term (Gini_c × FD_c) remains negative and maintains statistical significance at the 5% level ($\beta = -0.092$, $z = -2.01$). Although the absolute magnitude of the coefficient has slightly decreased compared to the original model (from -0.098 to -0.092), the stability of its sign confirms that the moderating role of inclusive finance is an independent and existing mechanism. FD truly weakens the link between inequality and pollution, and is not a spurious result of modeling misspecification.

5. DISCUSSION

5.1 Discussion of main results

The research findings have provided robust empirical evidence that income inequality is a factor that increases carbon intensity in emerging Asian economies. This finding is fully consistent with Boyce's [13] political economy theory of the environment, which posits that asymmetry in economic power translates into asymmetry in political power, where the wealthy elite can lobby to relax environmental regulations to protect the interests of resource-intensive industries. Empirically, our results align with previous studies such as Grunewald et al. [2] and Zhang and Zhao [20], who also found a positive relationship between inequality and carbon emissions. However, our study goes deeper by focusing on "carbon intensity," a more appropriate measure of energy efficiency for the context of developing countries, where the priority is not to trade off growth, but to reduce the emission level per unit of GDP generated.

The most unique and core contribution of this paper is the confirmation of the negative moderating role of inclusive FD. This finding significantly extends the work of Le et al. [17] and Duong and Flaherty [24]. While those studies suggested a direct impact of finance on the environment, our research, by using an interaction methodology and advanced econometric techniques (System GMM), has elucidated a more complex mechanism: finance not only has an independent effect but also changes the nature of the relationship between inequality and the environment. It acts as a "corrective mechanism" for market and institutional failures caused by inequality. Specifically, in a polarized society, inclusive finance becomes a tool that helps disadvantaged groups overcome capital barriers to access cleaner consumption and production options, thereby breaking the vicious cycle of poverty and pollution that the energy ladder theory pointed out [14].

5.2 In-depth analysis of marginal effects and policy threshold

The in-depth analysis of the threshold FD ≈ 0.509 reveals important policy implications, especially when placed in the practical context of the Asian region.

When this threshold value is compared with the sample characteristics (the mean value of the FD index is 0.384 in Table 2), a noteworthy reality emerges: the majority of emerging Asian economies in the research sample are currently operating in a zone where income inequality increases carbon emission intensity. This can be explained by the fact that in countries with insufficiently developed financial systems, low-income households lack access to "green" credit and financial instruments. Consequently, they may be trapped using energy-intensive, high-emission technologies, equipment, and vehicles, exacerbating the environmental impact of inequality.

This result confirms hypothesis H2 and carries strong policy implications. The downward slope of the marginal effect line indicates that as a country improves its level of FD, the negative environmental impact of inequality will gradually weaken. For example, raising the FD index from a low level (0.2) to near the threshold (0.5) could almost completely nullify this harmful effect. Therefore, in a context where addressing income inequality is a long-term challenge, promoting inclusive FD can be seen as an effective and feasible short-term policy tool to mitigate the environmental consequences of inequality.

5.3 In-depth analysis of heterogeneity between lower-middle income and upper-middle income country groups

The sub-sample analysis results show that both the negative impact of inequality and the positive moderating role of finance are stronger in the group of LMI countries. This is not surprising and is fully consistent with the theory of diminishing marginal returns.

Why is the impact of inequality more severe in the LMI group? In countries like Cambodia, Bangladesh, or Pakistan, inequality is not just a gap in lifestyle, but a gap in survival. The poor are forced to exploit depleting resources (deforestation for firewood) or use the cheapest and most toxic energy sources. Environmental governance institutions in these countries are also weaker, making the power of the elite to dominate policy even more pronounced.

Why is the moderating role of finance more effective in the LMI group? The environmental benefit of the first loan that helps a family switch from burning straw and coal to using gas is much greater than the benefit of the tenth loan that helps a middle-class family in Thailand switch from a gasoline scooter to an electric one. In the LMI group, inclusive finance is addressing the "low-hanging fruits" of the energy transition. A $100 loan for a water filtration system or a small solar panel in a remote village can create a much larger marginal impact on the environment and health than a green mortgage of tens of thousands of dollars in a developed city.

5.4 In-depth analysis of the non-linear relationship of finance

The robustness check results revealed an interesting finding: the direct relationship between FD and carbon intensity has a U-shape. In the initial stage, FD helps businesses access capital to improve efficiency and replace old machinery, thereby reducing carbon intensity (the downward-sloping part of the U). However, as the financial system becomes very developed, it can fuel a wave of mass consumption and large-scale industrial projects. Although these projects may be more technologically efficient, their absolute scale can slow down the rate of emission reduction, and even slightly increase carbon intensity in some sectors (the upward-sloping part of the U).

However, the most crucial point is that even after controlling for this complex relationship, the moderating role of finance remains statistically significant. This confirms that the moderating mechanism of finance on inequality is an independent channel of impact, not a spurious result of omitting non-linearity.

5.5 Contributions of the study

Our research contributes to the existing body of knowledge in two main aspects:

Theoretically: The work has successfully integrated the political economy theory of the Environment with Financial Intermediation Theory to build and test a moderation framework. This approach moves beyond traditional direct, linear impact models, providing a more multidimensional and realistic view of the complex relationship between society, finance, and the environment.

Empirically: This study is one of the first to simultaneously use superior datasets (SWIID, IMF FD Index) and robust econometric methods (System GMM, Driscoll-Kraay) to analyze this issue in the context of Asian countries. The rigorous handling of endogeneity and cross-sectional dependence enhances the reliability of the empirical results.

6. CONCLUSION

This study set out to examine whether inclusive FD can moderate the relationship between income inequality and carbon intensity in emerging Asian economies. By integrating the political economy theory of the Environment with Financial Intermediation Theory, the research has established and empirically validated a moderation framework that moves beyond the conventional approach of treating inequality and finance as independent determinants of environmental quality.

The evidence consistently supports both hypotheses across multiple estimation methods and robustness checks. Income inequality is confirmed as a driver of carbon intensity (H1), and inclusive FD is shown to act as a negative moderator that weakens this adverse link (H2). The identification of a policy-relevant threshold (FD $\approx$ 0.509) further reveals that most countries in the sample have not yet reached the level of FD necessary to neutralize the environmental harm of inequality.

These findings carry three important implications. *Theoretically,* the study reframes the inequality-environment relationship from a static, direct association to a conditional one, demonstrating that the environmental consequences of inequality are not predetermined but depend on the institutional context—specifically, the inclusiveness of the financial system. This perspective bridges a gap between the environmental inequality literature and the FD literature, offering a unified analytical lens. For policy, the results transform the perceived trade-off between social equity and environmental sustainability into a potential synergy. Rather than treating inequality reduction and emission mitigation as competing objectives, policymakers can leverage inclusive FD as a strategic instrument that serves both goals simultaneously. In practice, this means prioritizing the expansion of credit access and green financial products for low-income households and SMEs, particularly in lower-middle-income countries where the marginal impact of such interventions is greatest. Methodologically, the study demonstrates the value of combining superior datasets (SWIID for inequality, IMF FD Index for FD) with rigorous econometric techniques (System GMM, Driscoll-Kraay) and mean-centered interaction terms to produce reliable estimates in a panel setting prone to endogeneity and cross-sectional dependence.

Despite these contributions, the study has limitations that open avenues for future research. The analysis is based on macro-level national data and focuses exclusively on CO_2 emission intensity, which limits the ability to trace the micro-level transmission channels through which finance alters household or firm energy behavior. Future studies could employ household or firm-level survey data to directly test these mechanisms. Additionally, expanding the analysis to encompass broader environmental measures (e.g., ecological footprint, methane emissions) or disaggregating the roles of specific financial instruments (e.g., green credit, mobile banking, fintech) would further enrich the understanding of how inclusive finance can contribute to a sustainable and equitable development trajectory.

ACKNOWLEDGMENT

This research is partly funded by the Banking Academy of Vietnam, under the Grant No. 2500/HD-HVNH-VNC1.

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