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Nexus between Extreme Poverty and CO2 Emissions in Indonesia: An Empirical Investigation with VECM Approach

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Abstract: Two sustainable development goals, poverty reduction and environmental quality, present challenges in Indonesia. While extreme poverty in Indonesia declined from 1990 to 2022, CO2 emissions rose, making Indonesia vulnerable to achieving these goals. This study investigates the conflict between extreme poverty alleviation and environmental quality improvement as measured by CO2 emissions, focusing on the relationship between the two. Using 1990-2022 time series data and the Vector Error Correction Model (VECM) approach, the results show that economic growth reduces extreme poverty but increases CO2 emissions. In addition, improving human quality (HDI) reduces CO2 emissions and extreme poverty. These findings confirm the relationship between economic growth, poverty alleviation, and environmental quality. Therefore, the government must adjust its economic development policies to be environmentally friendly and support improving human quality to overcome this challenge.

Keywords: extreme poverty; CO2 emissions; economic growth; environmental quality
JEL Classification: C32; I32; Q44; Q53; Q56

Introduction

As the global economy develops, environmental pollution becomes increasingly severe (Guo et al., 2018, 2019; Guo & Zhou, 2020; Li et al., 2019; Zeng et al., 2019). The greenhouse effect caused by carbon dioxide (CO2) emissions has become one of the world's most alarming environmental issues (Jian et al., 2019). According to the International Energy Agency (IEA), global CO2 emissions will peak at 37.2 Gigatons in 2022. This is a 76.3% increase from 1990. The scientific community unanimously states that greenhouse gases are the leading cause of global warming. Water vapor, nitrogen dioxide, methane, and carbon dioxide are the main contributors to the greenhouse effect. However, of these, CO2 is the most prevalent gas in the atmosphere and poses a major threat to the environment (Ahmed et al., 2017). Thus, promoting the reduction of CO2 emissions is the responsibility of all countries in the world to address climate change due to global warming and achieve sustainable development goals (SDGs).

Environmental problems affect human well-being and sustainable development. The World Commission on Environment and Development (WECD, 1987) states that poverty is both a cause and effect of environmental degradation. People experiencing poverty rely heavily on natural resources to fulfill basic needs, leading to environmental degradation. Typically, the natural environment is considered a public good easily accessible and not protected by property rights (Baloch, Danish, Khan, & Ulucak, 2020a). This leads to unsustainable exploitation of environmental resources for survival. Therefore, increasing poverty has a negative impact on the environment, especially in developing countries (Masron & Subramaniam, 2019). On the other hand, poverty is also seen as a consequence of poor environmental quality. One of the leading causes of poverty is unsustainable development. Exploitation of natural resources without considering the environment, directly or indirectly, can negatively impact the sustainability of people's income and health, increasing poverty (Kartiasih & Pribadi, 2020).

Some are classified as extremely poor among all the people living below the poverty line or identified as poor. One of the government's commitments to alleviate extreme poverty is to announce Presidential Instruction Number 4 of 2022, which serves as the basis for alleviating extreme poverty six years ahead of the SDGs target. Thus, the Government of Indonesia targets extreme poverty at 0 percent by 2024. According to the United Nations (UN), extreme poverty is the welfare status of people living on less than $2,15 or the equivalent of around Rp35.224 per day or Rp1.056.720 per month. Research by Setyadharma et al. (2020) shows a reciprocal relationship between efforts to improve environmental quality and poverty. Government efforts to preserve the environment will limit the poor's ecological access. This will make it harder for people experiencing poverty, especially the very poor who rely heavily on the environment to escape poverty, and there is a greater risk that they will become even more vulnerable. However, this uncontrolled exploration will also cause environmental damage (Oktavilia et al., 2018).

One possible solution to reduce poverty is to formulate policies that support economic growth because policies that promote economic growth are assumed to benefit people experiencing poverty (Dhrifi et al., 2020). However, increasing economic growth also increases energy demand, damaging the environment and threatening sustainable development and human well-being (Baloch, Danish, Khan, & Ulucak, 2020a). In fact, one of the key sustainable development goals of the United Nations is to reduce additional pressure on natural resources and the environment as part of the development process (Haider et al., 2018). This suggests a conflict or trade-off relationship between sustainable development goals: poverty alleviation and environmental quality improvement. Some of the following studies prove that there is a trade-off relationship in efforts to alleviate poverty and improve environmental quality in various countries around the world (Baloch, Danish, Khan, & Ulucak, 2020b; Koçak & Çelik, 2022; Masron & Subramaniam, 2019).

Until now, it has been unclear what policies need to be synchronized at the global level to improve environmental quality and reduce poverty. We must consider the relationship between economic activity, poverty, and environmental quality to achieve sustainable development. Several studies show the relationship between poverty, economic growth, and CO2 emissions. There are three research types: the first focuses on the relationship between poverty and environmental quality. Research by Kartiasih & Pribadi (2020)successfully proved that poverty can affect ecological degradation. In addition, research by Baloch, Danish, Khan, Ulucak, et al. (2020) demonstrated that poverty contributes to increased CO2 emissions. The second study focused on the relationship between economic growth and carbon dioxide emissions. The study conducted by Fodha & Zaghdoud (2010)showed that there is a long-term cointegration relationship between carbon dioxide emissions and GDP. This study also supports the Environmental Kuznets Curve (EKC) approach, which states that an increase in environmental pollution only occurs at the beginning of the economic expansion phase. The ongoing process of economic development can structurally affect ecology along with technological advancements. In the development process, using natural resources from the environment will be more prudent, environmental awareness will also increase, and clean technology and innovation will emerge as structural effects. The following studies also provide results that support the EKC approach (Baek, 2016; Bölük & Mert, 2015; Lee & Oh, 2015; Shujah-ur-Rahman et al., 2019). The third part places all three variables, namely economic growth, poverty, and carbon dioxide (CO2) emissions, under the same framework to study dynamic cause-and-effect relationships. Recent studies show a dilemma between reducing rural poverty and improving environmental quality, proving that economic growth supports alleviating rural poor (Do Miswa & Kartiasih, 2025).

Indonesia is a country with a growing economy. Figure 1 shows that Indonesia's GDP has continued to increase from 1990 to 2022, although it declined in 1998 and 2020. In addition, Indonesia is the only Southeast Asian economy in the world's top 15 with a nominal GDP of 1.1 trillion USD (Kartiasih & Pribadi, 2020). In line with the economic improvement, extreme poverty in Indonesia continues to decline from a high of almost 70% in 1998 to 2,17% in 2022. As illustrated in Figure 2, the percentage of Indonesia's extreme poor population has declined sharply over time, reflecting the success of economic growth in improving living standards. This shows that Indonesia has successfully reduced poverty by promoting economic growth. However, Indonesia's carbon dioxide (CO2) emissions continue to increase from 155 Megatons in 1990 to more than 700 Megatons in 2022. Figure 3 supports this trend, showing a steady and significant rise in CO_2 emissions throughout the same period, signaling increasing environmental pressure due to economic activities. This aligns with Grunewald et al.'s (2017)research, which states that income can reduce poverty but increase environmental problems. In addition, economic initiatives aimed at reducing poverty cause ecological damage in Indonesia because Indonesia's current energy supply system is still based on fossil fuels (Kartiasih & Pribadi, 2020). These regional dynamics also align with findings by Hasanah and Wu (2023), which emphasize the importance of spatially adaptive environmental policies in reducing emission disparities across Indonesian provinces. This makes Indonesia a vulnerable country in achieving the Sustainable Development Goals.

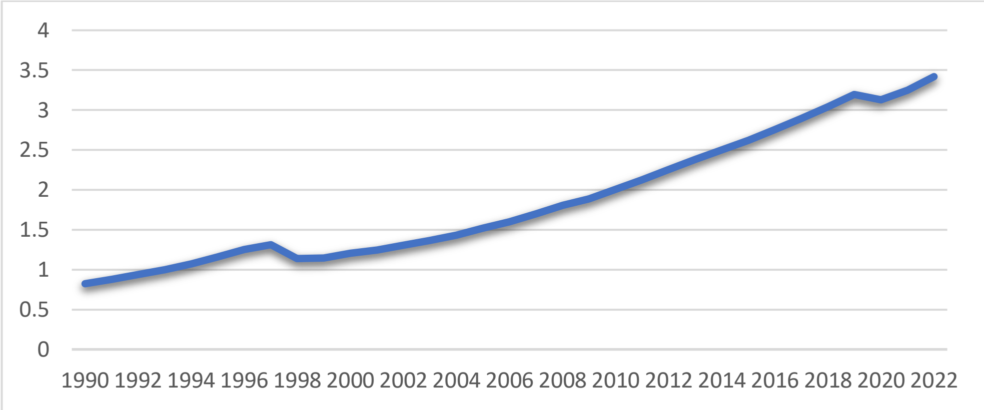

Figure 1 Indonesia's ADHK Gross Domestic Product (Trillion USD) for the Period 1990 to 2022
Source: World Bank (2022), processed

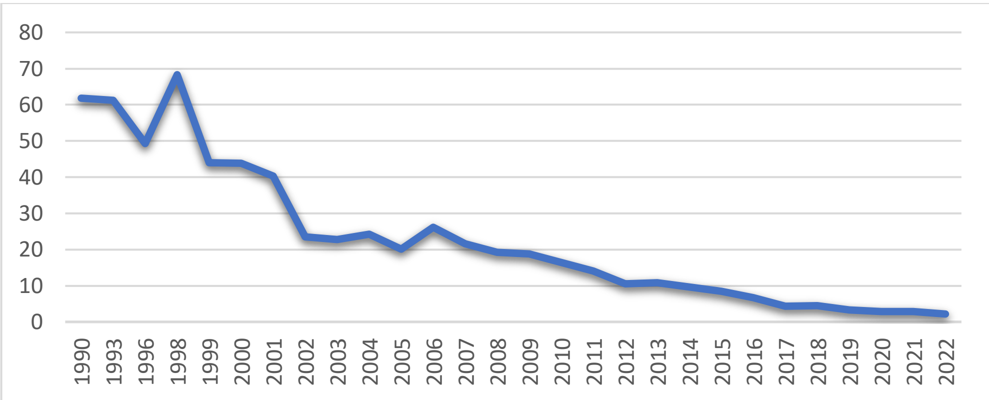

Figure 2 Percentage of Indonesia's Extreme Poor Population for the Period 1990 to 2022
Source: Our World in Data (2022), processed.

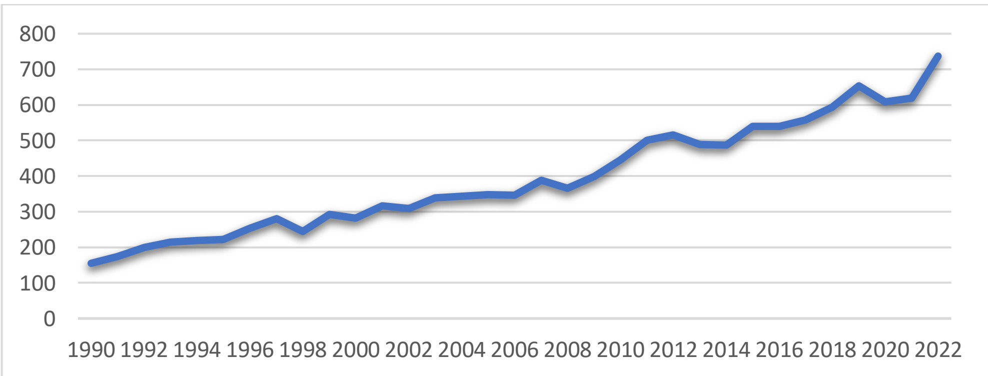

Figure 3 Indonesia's Carbon Dioxide Emissions (Megatons) for the Period 1990 to 2022

This study uses annual time series data for Indonesia from 1990 to 2022, corresponding to an observation period of 33 years. The data used includes four secondary variables, namely carbon dioxide emissions (a key indicator of the environmental impact of economic activity), economic growth (measured by gross domestic product (GDP), which represents the country's economic performance), the human development index (which describes people's quality of life), and extreme poverty. The main data source used in this study is Our World in Data, which provides open and reliable data for cross-country and long-term analysis. In this study, Johansen covariance test, Granger causality test, and vector error correction model (VECM) are used to analyze the impact of economic growth, human development index (HDI), and extreme poverty shocks on carbon dioxide (CO2) emissions and to assess the contribution of these three variables to CO2 emissions.

Based on the problems described, this study investigates the conflict between extreme poverty alleviation and environmental quality improvement measured by CO2 emissions. This investigation is conducted by looking at the impact of economic growth on CO2 emissions and the impact of economic growth on extreme poverty. Furthermore, it estimates the impact of HDI variables as a measure of human quality. Ultimately, this study aims to answer the following questions: (i) Is there a trade-off or conflict between extreme poverty and environmental quality? (ii) Can human development (HDI) reduce extreme poverty and improve environmental quality, as measured by reduced CO2 emissions?.

This study offers several novel contributions to the existing literature on the nexus between economic growth, human development, poverty alleviation, and environmental quality. First, while many previous studies have explored the relationship between these variables using a panel data approach, this research focuses exclusively on Indonesia by employing an extended annual time series dataset from 1990 to 2022. This country-specific and time-extensive perspective enables a deeper understanding of structural dynamics unique to Indonesia as a rapidly developing economy. Second, the study examines the interaction among economic growth, human development index (HDI), extreme poverty, and carbon dioxide (CO_2) emissions simultaneously—an integrated approach rarely found in prior research that typically treats these variables in isolation or in partial relationships. Third, the Vector Error Correction Model identifies short-run adjustments and long-run equilibrium relationships, offering more comprehensive insight into causal mechanisms. Lastly, by aligning its analysis with the SDGs, particularly Goal 1 (No Poverty) and Goal 13 (Climate Action), this study contributes empirical evidence to policy debates on whether human development and poverty alleviation can be achieved without exacerbating environmental degradation.

In addition, recent studies in Indonesia also confirm the urgency of integrating poverty alleviation and environmental sustainability in policy design, particularly in regions with significant ecological vulnerability (Hasanah & Wu, 2023). The remainder of this study is structured as follows: Section 2 explores the literature on the relationship between extreme poverty, economic growth, and CO2 emissions. Section 3 outlines the data and methodology used in the study. Section 4 presents the findings, analysis, and associated policy implications. Finally, section 5 discusses the research conclusions and provides recommendations for future studies.

Research Method

This study uses annual time series data for Indonesia from 1990 to 2022, corresponding to an observation period of 33 years. The data used includes four secondary variables, namely carbon dioxide emissions (a key indicator of the environmental impact of economic activity), economic growth (measured by gross domestic product (GDP), which represents the country's economic performance), the human development index (which describes people's quality of life), and extreme poverty. The main data source used in this study is Our World in Data, which provides open and reliable data for cross-country and long-term analysis.

In this study, Johansen covariance test, Granger causality test, and vector error correction model (VECM) are used to analyze the impact of economic growth, human development index (HDI), and extreme poverty shocks on carbon dioxide (CO2) emissions and to assess the contribution of these three variables to CO2 emissions. Since most time series data are unstable, using direct regression may lead to pseudo-regression. Therefore, Engle and Granger proposed the concept of cointegration, which is the existence of a stable long-term relationship between economic variables.

This approach was later developed by Sims and Watson for multivariate modeling of variables with unit roots. Based on these developments, the VECM model was formally proposed and is now widely used to study long-run equilibrium relationships and short-run dynamic relationships among variables with cointegration. The VECM provides a rich structure for understanding dynamic interactions between variables through impulse response analysis and variance decomposition (Lütkepohl, 2005). If the variables in this study are cointegrated, then the VECM equation can be expressed as follows:

$\Delta lnCO_2$ Model:

$$\Delta lnCO_{2t} = \sum_{i=1}^{n} \alpha_{1i}\, \Delta lnCO_{2t-i} + \sum_{j=1}^{n} \beta_{1j}\, \Delta lnHDI_{t-j} + \sum_{k=1}^{n} \gamma_{1k}\, \Delta lnGDP_{t-k} + \sum_{l=1}^{n} \delta_{1l}\, \Delta lnExtremePoverty_{t-l} + \xi_1\, ECT_{t-1} + \mu_{1t}$$

ΔlnHDI Model

$$\Delta lnHDI_{t} = \sum_{i=1}^{n} \alpha_{2i}\, \Delta lnCO_{2t-i} + \sum_{j=1}^{n} \beta_{2j}\, \Delta lnHDI_{t-j} + \sum_{k=1}^{n} \gamma_{2k}\, \Delta lnGDP_{t-k} + \sum_{l=1}^{n} \delta_{2l}\, \Delta lnExtremePoverty_{t-l} + \xi_2\, ECT_{t-1} + \mu_{2t}$$

ΔlnGDP Model

$$\Delta lnGDP_{t} = \sum_{i=1}^{n} \alpha_{3i}\, \Delta lnCO_{2t-i} + \sum_{j=1}^{n} \beta_{3j}\, \Delta lnHDI_{t-j} + \sum_{k=1}^{n} \gamma_{3k}\, \Delta lnGDP_{t-k} + \sum_{l=1}^{n} \delta_{3l}\, \Delta lnExtremePoverty_{t-l} + \xi_3\, ECT_{t-1} + \mu_{3t}$$

ΔlnExtremePoverty Model

$$\Delta lnExtremePoverty_{t} = \sum_{i=1}^{n} \alpha_{4i}\, \Delta lnCO_{2t-i} + \sum_{j=1}^{n} \beta_{4j}\, \Delta lnHDI_{t-j} + \sum_{k=1}^{n} \gamma_{4k}\, \Delta lnGDP_{t-k} + \sum_{l=1}^{n} \delta_{4l}\, \Delta lnExtremePoverty_{t-l} + \xi_{4}\, ECT_{t-1} + \mu_{4t}$$

In this model, μ, α, β, γ, and δ are coefficients, and ECTt-1 represents CO2 emissions. For example, equation (1) tests the causal relationship between LNGDP and LNCO2 on extreme poverty. Suppose the null hypothesis (H0: β1j = γ1k = 0) in equation (1) is rejected. In that case, it implies the existence of short-run Granger causality between LNGDP and LNCO2 and extreme poverty.

The coefficient ε1 of the error correction term (ECT) indicates how quickly the variable returns to long-run equilibrium. Suppose the negative hypothesis (H0: ε1 = 0) is rejected. In that case, there is long-run Granger causality from the variables on the right-hand side of the equation to those on the left-hand side.

Recent literature suggests that Granger causality methods, including causality tests using VECM Granger, have some limitations. One drawback is the inability to measure the relative strength of the causal relationship between variables beyond the analyzed time period, thus reducing the confidence in the results obtained. In addition, this method does not provide information on the relative contribution of each variable.

Result and Discussion

Unit Root Analysis

All variables used in this study are time series variables, so it is necessary to conduct a unit root test for each variable before performing the analysis to avoid the phenomenon of pseudo-regression. This study uses the Augmented Dickey Fuller (ADF) test, and the ADF test results are shown in Table 1. Table 1 shows that the ADF values of CO2 emissions, economic growth, and extreme poverty have p-values more than the significance level of 5%, thus failing the null hypothesis. Therefore, the null hypothesis stating the existence of unit roots fails to be rejected, which indicates that with a significance level of 5%, there is not enough evidence to show that the variables of CO2 emissions, economic growth, and extreme poverty are stationary at the level, so it is necessary to test stationarity at the first difference. After the test, with a significance level of 5%, there is enough evidence to show that the variables of CO2 emissions, economic growth, and extreme poverty are stationary in the first difference.

Meanwhile, the ADF value of HDI has a p-value more than the significance level of 5%, thus rejecting the null hypothesis. Therefore, the null hypothesis that there is a unit root is rejected, which indicates that with a 5% significance level, there is enough evidence to show that the HDI variable is stationary at the level and first difference. Thus, all variables are I(1). All variables are I(1), which means all variables are stationary after first differencing.

Table 1 Unit root test results

Variables	Test Type	ADF	5% Critical Value	P-Value	Results
lnCO2	C	-1.262145	-2.960411	0.6342	non-stationary
D(lnCO2)	C	-7.648991	-2.960411	0.0000	stationary
lnHDI	C	-3.325401	-2.957110	0.0219	stationary
D(lnHDI)	C	-4.155283	-2.960411	0.0029	stationary
lnGDP	C	-0.295688	-2.960411	0.9146	non-stationary
D(lnGDP)	C	-4.216364	-2.960411	0.0025	stationary
lnExtremePoverty	C	1.445021	-2.960411	0.9987	non-stationary
D(lnExtremePoverty)	C	-6.385052	-2.960411	0.0000	stationary

Optimum Interval/Lag Selection and VAR Stability Testing

Table 2 shows the selection of the optimum lag order based on the LogL, Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information (SC), and Hannan-Quinn Information Criterion (HQ) criteria. Table 2 shows lag 2 as the optimum lag based on the LogL criterion. Based on the following output, it can be seen that at lag 2, the LogL value is the most significant value, so the next lag we use is lag 2.

Table 2 VAR Lag Order Selection Criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	215.1169	NA	9.07e-12	-14.07446	-13.88763	-14.01469
1	229.3165	23.66601	1.04e-11	-13.95443	-13.02030	-13.65560
2	240.1612*	15.18261	1.56e-11	-13.61075	-11.92931	-13.07284

Notes: * indicates largest LogL; LR: modified LR test statistic in order (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion

Table 3 shows that the value of the roots of the polynomial function or modulus is less than 1, so the VAR system is stable at lag 2. Thus, Impulse Response Function (IRF) analysis and Forecast Error Decomposition Variance (FEDV) analysis are valid.

Table 3 Lag 2 VAR Stability Check

Root (Lag 1)	Modulus (Lag 2)
-0.300741 - 0.628243i	0.696516
-0.300741 + 0.628243i	0.696516
0.537067 - 0.069762i	0.541579
0.537067 + 0.069762i	0.541579
-0.037615 - 0.525399i	0.526743
-0.037615 + 0.525399i	0.526743
-0.401239	0.401239
0.082491	0.082491

Johansen Cointegration Test

After conducting the unit root test, all variables are known to be stationary series at first-order differentiation, so there is a possibility of a cointegration relationship between variables. This study uses the Johansen cointegration test method to test the existence of cointegration in the time series.

Before carrying out the cointegration test, the optimal lag length is determined thoroughly based on the AIC, SC, LR, FPE, and HQ criteria. Based on Table 3, the optimal lag length used in this study is 2. At the same time, the specific Johansen cointegration test results are presented in Table 4.

Table 4 Johansen Cointegration Test Results.

Null Hypothesis	Trace Statistic	5% Critical Value	Prob. **
R = 0*	63.79292	54.07904	0.0054
R ≤ 1	33.94831	35.19275	0.0677
R ≤ 2	16.29869	20.26184	0.1609
R ≤ 3	5.388321	9.164546	0.2435

Notes: Trace test indicates 1 cointegrating equation at 0.05 level; * indicates hypothesis rejection at 0.05 level; ** MacKinnon-Haug-Michelis (1999) p-value

The Johansen cointegration test is the trace statistic, as seen in Table 4. In the trace statistic method, the null hypothesis, which states the absence of cointegration, is rejected if the p value is smaller than 0.05 at the 5% significance level. However, the method cannot reject the null hypothesis (R ≤ 1), which indicates that there is only a maximum of one cointegrating relationship at the 5% significance level. Therefore, there is a cointegrating relationship between CO_2 emissions, HDI, economic growth, and extreme poverty.

Granger Causality Test

After determining a cointegration relationship between variables through the Johansen Cointegration Test, the next step is to test the causal relationship between variables in the VAR system. The causal relationship is examined through the application of the Granger Causality Test, as described in this section.

Table 5 Granger Causality Test Results

Variables	Granger Causality Type				
	Short Term				Long Term
	D(lnCO2)	D(lnHDI)	D(lnGDP)	D(lnExtreme Poverty)	ECTt-1
D(lnCO2)		0.44697 [0.6444]	0.43348 [0.6529]	1.28473 [0.2937]	1.000000
D(lnHDI)	3.24326* [0.0553]		0.95253 [0.3988]	2.88351* [0.0740]	-4.433494 [-2.26834]
D(lnGDP)	2.05107 [0.1489]	2.49938 [0.1017]		2.30808 [0.1195]	0.328406 [0.50907]
D(lnExtreme Poverty)	1.90233 [0.1694]	0.30252 [0.7415]	1.41133 [0.2619]		0.494402 [2.62603]

Notes: In the short-term causality test, the F-statistic value is used, and the value in square brackets is the corresponding p-value; In the long-term causality test, the t-statistic is provided in square brackets; *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively; > means that the left side can cause the right side; ≠> implies that the left side cannot cause the right side.

VECM Model Formation

Based on the Johansen cointegration test output, the variables are cointegrated. We use the vector error correction model (VECM) framework described below. Granger pointed out that the vector error method (VECM) is more appropriate for testing causality between series if the variables are I(1) integrated (Granger, 2002).

Table 6 Estimation of Vector Error Correction

Error Correction	D(lnCO2)	D(lnHDI)	D(lnGDP)	D(lnExtreme Poverty)
ECTt-1	0.079497 (0.07536) [1.05494]	0.024817 (0.00599) [4.14044]	0.053475 (0.03841) [1.39205]	-0.071877 (0.19481) [-0.36895]
D(lnCO2(-1))	-0.443273 (0.28049) [-1.58036]	-0.043145 (0.02231) [-1.93387]	-0.193417 (0.14298) [-1.35272]	-0.539212 (0.72512)[- 0.74361]
D(lnHDI(-1))	-2.475336 (3.63749) [-0.68051]	-0.550272 (0.28933) [-1.90190]	-2.209451 (1.85427) [-1.19155]	11.23706 (9.40370) [1.19496]
D(lnHDI(-2))	2.613933 (3.43422) [0.76114]	-0.275798 (0.27316) [-1.00966}	1.505598 (1.75065) [0.86065]	-9.284595 (8.87820) [-1.04572]
D(lnGDP(-1))	0.193483 (0.56190) [0.34434]	0.134007 (0.04469) [2.99831]	0.566493 (0.28644) [1.97770]	0.483329 (1.483329) [0.33272]
D(lnGDP(-2))	0.29108 (0.66171) [0.43992]	0.084295 (0.05263) [1.60157]	0.183711 (0.33732) [0.54462]	-1.215587 (1.71067) [-0.71059]
D(lnPovertyExtremes(-1))	-0.085969 (0.09776) [-0.87939]	-0.019555 (0.00778) [-2.51474]	-0.125074 (0.04984) [-2.50974]	0.202502 (0.25273) [0.80125]
D(lnExtreme Poverty (-2))	-0.146284 (0.09954) [-1.46955]	-0.004154 (0.00792) [-0.52585]	-0.048184 (0.05074) [-0.94955]	0.139643 (0.25734) [0.54294]
R-squared	0.174223	0.476639	0.21604	0.024715
Adj R-Squared	-0.140345	0.277263	-0.087356	-0.346822
F-statistic	0.553862	2.390659	0.708775	0.066

Note: t-statistics are provided in square brackets

Based on tables 5 and 6, it can be seen that there is either an effect or no effect between variables. Based on the estimation results, if t-count > t-table, there is an effect. It can be concluded that HDI and Extreme Poverty significantly impact the long run, as indicated by the significant coefficient of Error Correction Term (ECTt-1). This shows that both variables play a role in the adjustment process towards the long-run equilibrium. In contrast, the GDP variable does not show any correction towards the long-run (insignificant coefficient).

Meanwhile, in the short term, it shows that with a significance level of 10%, the HDI variable significantly affects CO2 and Extreme Poverty. In contrast, CO2, GDP, and

Extreme Poverty do not show a significant direct effect. This suggests that the impact of the relationship between variables is more dominant in the long run than in the short run. The overall model explanation is still weak, indicating the need to consider other factors or additional models for a more in-depth analysis.

Therefore, the best model is HDI with the highest R-squared (47.66%) and the most significant F-statistic (2.39); this model best explains the relationship between variables in VECM. In addition, the VECM model equation is obtained as follows:

$$\begin{aligned}\Delta \ln CO_{2t} = {} & 0{,}0795 * \text{Cointegration Eq.1} \\ & - 0{,}4433 * \Delta \ln CO_{2t-1} - 0{,}4064 * \Delta \ln CO_{2t-2} \\ & - 2{,}4753 * \Delta \ln HDI_{t-1} + 2{,}6139 * \Delta \ln HDI_{t-2} \\ & - 0{,}1935 * \Delta \ln GDP_{t-1} + 0{,}2911 * \Delta \ln GDP_{t-2} \\ & - 0{,}0860 * \Delta \ln ExtremePoverty_{t-1} - 0{,}1463 * \Delta \ln ExtremePoverty_{t-2}\end{aligned}$$

$$\begin{aligned}\Delta \ln HDI_{t} = {} & 0{,}0248 * \text{Cointegration Eq.1} \\ & - 0{,}0431 * \Delta \ln CO_{2t-1} - 0{,}0271 * \Delta \ln CO_{2t-2} \\ & - 0{,}5503 * \Delta \ln HDI_{t-1} - 0{,}2758 * \Delta \ln HDI_{t-2} \\ & - 0{,}1340 * \Delta \ln GDP_{t-1} + 0{,}0843 * \Delta \ln GDP_{t-2} \\ & - 0{,}0195 * \Delta \ln ExtremePoverty_{t-1} - 0{,}0042 * \Delta \ln ExtremePoverty_{t-2}\end{aligned}$$

$$\begin{aligned}\Delta \ln GDP_{t} = {} & 0{,}0535 * \text{Cointegration Eq.1} \\ & - 0{,}1934 * \Delta \ln CO_{2t-1} - 0{,}2949 * \Delta \ln CO_{2t-2} \\ & - 2{,}2094 * \Delta \ln HDI_{t-1} + 1{,}5067 * \Delta \ln HDI_{t-2} \\ & + 0{,}5665 * \Delta \ln GDP_{t-1} + 0{,}1837 * \Delta \ln GDP_{t-2} \\ & - 0{,}1251 * \Delta \ln ExtremePoverty_{t-1} - 0{,}0482 * \Delta \ln ExtremePoverty_{t-2}\end{aligned}$$

$$\begin{aligned}\Delta \ln ExtremePoverty_{t} = {} & - 0{,}0719 * \text{Cointegration Eq.1} \\ & - 0{,}5392 * \Delta \ln CO_{2t-1} - 0{,}4553 * \Delta \ln CO_{2t-2} \\ & - 11{,}2371 * \Delta \ln HDI_{t-1} - 9{,}2846 * \Delta \ln HDI_{t-2} \\ & - 0{,}4833 * \Delta \ln GDP_{t-1} - 1{,}2156 * \Delta \ln GDP_{t-2} \\ & - 0{,}2025 * \Delta \ln ExtremePoverty_{t-1} - 0{,}1396 * \Delta \ln ExtremePoverty_{t-2}\end{aligned}$$

Cointegration Equation (Eq.1):

$$\ln CO_{2t-1} - 4{,}4335 * \ln HDI_{t-1} + 0{,}3284 * \ln GDP_{t-1} + 0{,}4944 * \ln ExtremePoverty_{t-1} - 32{,}1176$$

Impulse Response Function (IRF)

Figure 4a shows the impulse response of CO2 emissions to a one standard deviation shock to economic growth. The response of CO2 emissions is positive to shocks coming from economic growth, reflecting that shocks to economic growth will increase CO2 emissions. Thus, changes in economic growth will continue to increase CO2 emissions for the next eleven or twelve years. This aligns with research conducted by Raihan et al. (2024), who proved a positive correlation between carbon emissions and economic growth in Vietnam. Although CO2 emissions will eventually decline according to Figure 5a, the decline will take over a decade. This suggests that Indonesia needs immediate and comprehensive policy adjustments to prevent environmental damage while maintaining economic progress. The Indonesian government must establish strong legal mechanisms and regulations to limit excessive carbon use while promoting sustainable development principles. One strategy that can be implemented is to encourage companies to use low-carbon production methods and internalize the social costs of pollution. This can be done through the implementation of a carbon tax. In addition, the environmental impact of economic activity can be reduced by investing in research and development of innovative technologies, such as carbon capture and storage technologies. Indonesia needs to increase international cooperation in order to gain benefits, such as knowledge exchange, which can strengthen efforts to combat climate change. On the other hand, there needs to be socialization to increase public awareness, and education is also crucial to raise public awareness of the environment.

Figure 4b shows the impact of a one standard deviation shock to extreme poverty on the impulse response of CO2 emissions. The reaction of CO2 emissions is negative to shocks from extreme poverty from the second year of the shock until year 10. However, the response of CO2 emissions started to be positive to shocks from extreme poverty in the 11th year of the shock. This reflects that shocks to extreme poverty in Indonesia will increase CO2 emissions from year 11 onwards. Thus, changes in extreme poverty will continue to increase CO2 emissions from year 11 onwards. This is due to the increase in the response of CO2 emissions, which shows a continuous increase because it does not converge to an equilibrium point (point zero). This result aligns with research by Baloch, Danish, Khan, Ulucak, et al. (2020), which proves that poverty contributes to increased carbon dioxide (CO2) emissions.

Figure 4c shows the impact of a one standard deviation shock to HDI on the impulse response of CO2 emissions. Initially, the impulse response of CO2 emissions is positive until year 13 to the shock from HDI. However, the impulse response of CO2 emissions starts to be negative from year 14 of the disturbance onwards to shocks originating from HDI. This reflects that shocks to HDI in Indonesia will reduce CO2 emissions from the 14th year of disturbance in Indonesia. Thus, changes in HDI will continue to reduce CO2 emissions from year 14 onwards. This is due to the increase in the CO2 emission response, which shows a continuous increase because it does not converge to an equilibrium point. This finding is consistent with (Koçak & Çelik, 2022), which states that HDI shows a decreasing influence on PM 2.5, representing environmental quality. Thus, the higher the human quality, the higher the environmental quality.

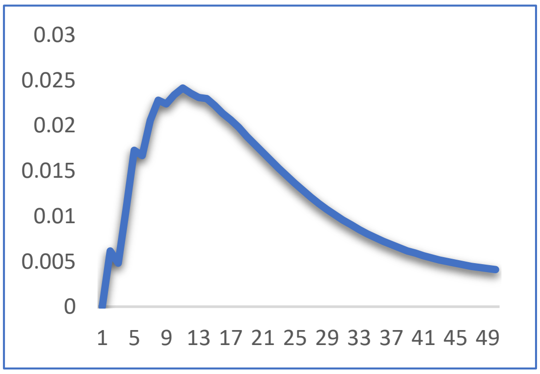

Figure 4a Response of lnCO2 to lnGDP

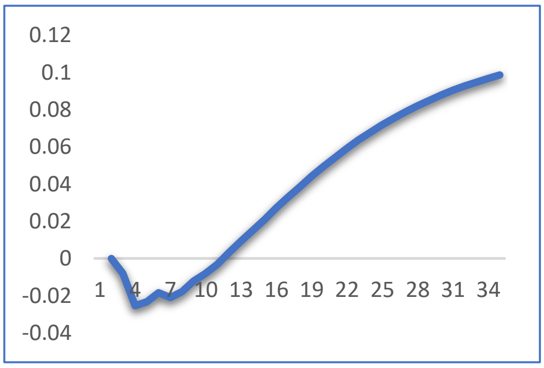

Figure 4b Response of lnCO2 to lnExtremePoverty

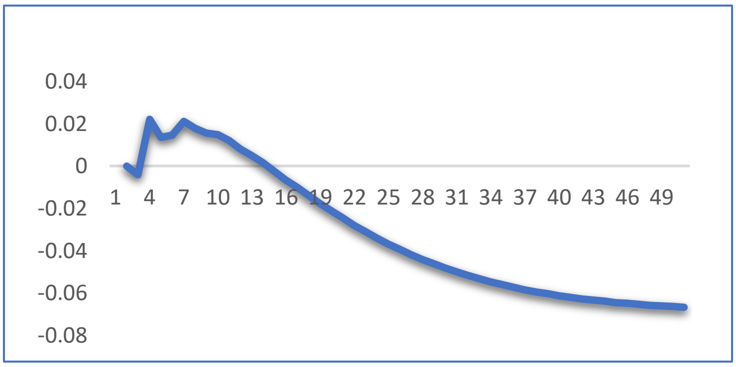

Figure 4c Response of lnCO2 to lnHDI

Figure 5a shows the impact of economic growth shocks on extreme poverty. In the first year of the shock, extreme poverty does not respond to economic growth shocks. Then, extreme poverty responds positively to economic growth shocks until the fourth year. Then, extreme poverty responds negatively to shocks from economic growth from the fifth year onwards. This negative extreme poverty response reflects that shocks to economic growth have reduced extreme poverty in Indonesia since the fifth year. This suggests that changes in economic growth reduce extreme poverty. This finding increases the validity of the importance of economic growth to reduce poverty, as many studies have proven (Afzal et al., n.d.; Ebunoluwa & Yusuf, n.d.; Garza-Rodriguez, 2018). This reflects that the policies formulated by the government to boost the Indonesian economy have succeeded in reducing extreme poverty in Indonesia. Thus, the government must promote economic growth that reduces poverty without increasing carbon emissions by focusing on developing green economy sectors, such as renewable energy and sustainable waste management.

Figure 5b shows the impact of HDI shocks on extreme poverty. The response to extreme poverty is negative to a shock of one standard deviation derived from HDI since the first year of the shock. The negative extreme poverty response reflects that shocks to HDI reduce extreme poverty in Indonesia. This shows that changes in HDI reduce extreme poverty in Indonesia. This is because the higher quality of human resources can significantly reduce the poverty rate (Widiastuti et al., 2022).

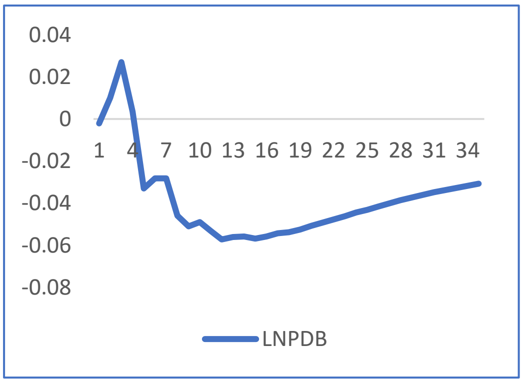

Figure 5a Response of lnExtreme Poverty to lnGDP

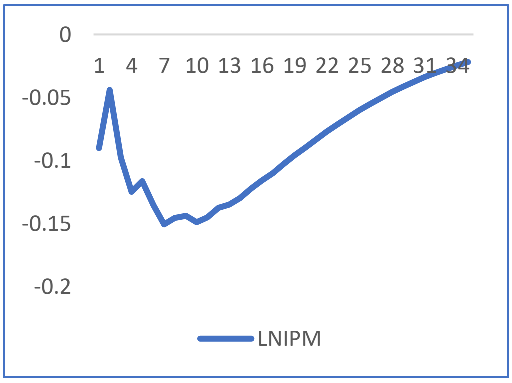

Figure 5b Response of lnExtreme Poverty to lnHDI

These results support the notion that economic-environmental trade-offs are highly contextual and must be addressed through localized policy approaches, as Hasanah and Wu (2023) argued in their analysis of Indonesia's regional carbon governance using a spatial sustainability framework. Overall, the impulse response function analysis results prove a trade-off relationship between efforts to alleviate extreme poverty and improve environmental quality as measured by the reduction in carbon dioxide emissions in Indonesia. The analysis shows that changes or increases in economic growth reduce extreme poverty in Indonesia. However, changes that occur due to shocks to economic growth increase CO2 emissions, which negatively impact environmental quality. This indicates that economic development in Indonesia, which aims to reduce poverty, causes environmental damage because Indonesia's energy supply system is still based on fossil fuels (Kartiasih & Pribadi, 2020). In addition, the analysis results prove that human quality, as measured by HDI, reduces extreme poverty and CO2 emissions. Thus, the higher the human quality in Indonesia, the lower the extreme poverty and CO2 emissions in Indonesia.

Forecast Error Variance Decomposition (FEVD)

First, the FEVD analysis focuses on the contribution of economic growth and extreme poverty to the forecast error variability of CO2 emissions in the next 35 years in Indonesia after the shock, as shown in Figure 6. In the first year, the forecast error variability of CO2 emissions is still entirely influenced by CO2 emissions. The contributions of economic growth, extreme poverty, and HDI only become apparent in the second year after the shock. The contribution of CO2 emissions decreases as the contribution of economic growth, extreme poverty, and HDI increases. In the next 35 years, there is a projected shift in the contribution to CO2 emissions from CO2 emissions to extreme poverty. This shift indicates the growing relevance of poverty-related emissions over time, highlighting the role of socioeconomic vulnerability in shaping future carbon trajectories—a concern emphasized by Hasanah and Wu (2023) in their spatial analysis of poverty-emission dynamics across Indonesia's diverse regions. Therefore, extreme poverty in Indonesia is the most crucial factor influencing CO2 emissions in the next 3 decades.

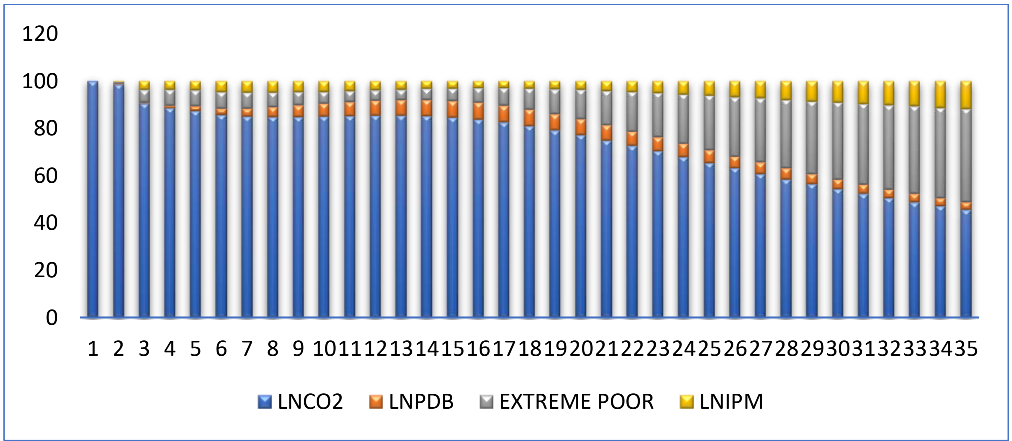

Figure 6 Decomposition results for CO2 emissions

Second, the FEVD analysis focuses on the contribution of economic growth, CO2 emissions, and HDI variables to the variability of the forecast error of extreme poverty in the next 35 years after a shock, as shown in Figure 7. The contribution of CO2 emissions and HDI was apparent in the first year. However, economic growth has a small contribution to the forecast error variability of extreme poverty in Indonesia in the next 35 years. In addition, the contribution of extreme poverty to itself continues to decrease as the contribution of CO2 emissions and HDI increases in the next 3 decades. However, the contribution of extreme poverty itself still dominates for the next 35 years. Thus, extreme poverty in Indonesia will become the most crucial variable influencing it in the next 3 decades.

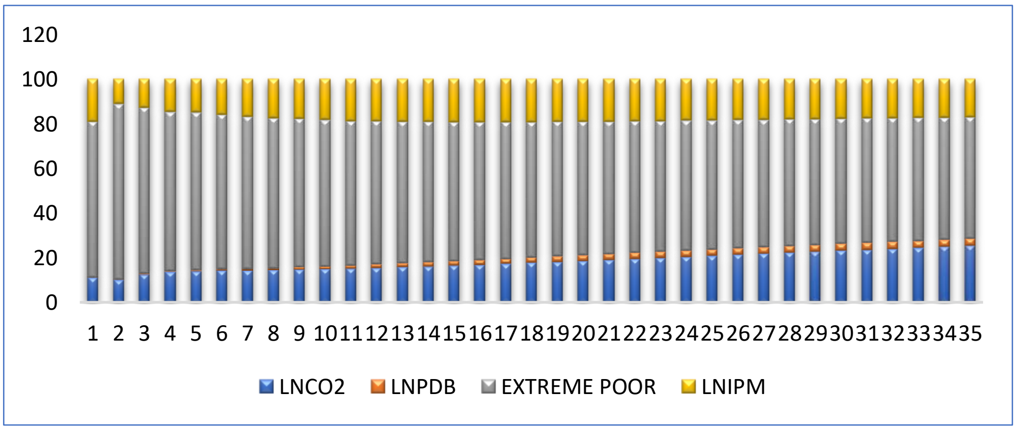

Figure 7 Decomposition results for Extreme Poverty

Conclusion

This study aims to analyze the impact of economic growth and extreme poverty on CO2 emissions and the impact of economic growth and CO2 emissions on extreme poverty to see the trade-off in efforts to alleviate extreme poverty and improve environmental quality. This research proves that there is a conflict between the goal of poverty alleviation by promoting economic growth and improving environmental quality, as measured by reducing CO2 emissions in Indonesia. This research proves that positive economic growth has reduced the percentage of extremely poor people in Indonesia. However, economic development in Indonesia has led to increased CO2 emissions that cause global warming. In addition, this study proves that human quality, as measured by HDI, supports improving environmental quality as measured by CO2 emission reduction and helps alleviate extreme poverty in Indonesia.

This study provides recommendations for the Indonesian government to limit the use of carbon-emitting energy to promote sustainable development principles, such as implementing a carbon tax. In addition, the government needs to invest in research and development of innovative technologies, such as carbon capture and storage technologies. In addition, the government needs to focus on developing the quality of human capital to increase environmental awareness and reduce extreme poverty in Indonesia.

This study contributes to the literature, but it has some limitations. First, this study only uses an indicator of air pollution to measure environmental quality. Environmental degradation considers various factors, including water pollution, deforestation, and land degradation, to better capture the phenomenon of environmental quality in Indonesia. Furthermore, this study only examines Indonesia, where the conclusions of this study may not be suitable for use in other countries around the world.

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