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Effect of Green Investment, Renewable Energy Consumption, and Carbon Tax Policies on Ecological Sustainability: Evidence from ASEAN Countries

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ABSTRACT

In this study, the implications of green investment, renewable energy consumption, and carbon tax policies on ecological sustainability in ASEAN countries for the period 2001-2024 are examined. The ecological footprint per person is the main indicator for environmental burden. The independent variables include carbon pricing (proxied by GDP deflator), renewable energy consumption and green investment proxied by domestic lending to the private sector as a percentage of GDP. The control variables used are digitalization (% of the population utilizing the internet) and foreign direct investment (FDI/GDP). We employ panel unit root tests (CIPS and CADF) to test for stationarity and the Westerlund cointegration test to test for the long-term relationship. The long run coefficients are estimated via Augmented Mean Group Estimator (AMG) and the Common Correlated Effects Mean Group Estimator (CCEMG) that take into account cross-sectional dependence and heterogeneous slopes. The results reveal that renewable energy use and green investment are significantly associated with environmental footprints, while carbon price moderates environmental degradation. Digitalization has a good influence on sustainability while FDI has a varying impact on sustainability depending on the absorptive capability of the host country. The findings have important policy implications for ASEAN officials engaged in the green transition process under the Paris Agreement and the regional sustainability agenda.

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Introduction

In the face of environmental degradation, mainly caused by industrialization, dependence on fossil fuels, and mismanagement of environmental resources, ecological sustainability is gradually becoming a prominent issue on the global policy agenda. The ASEAN region, which consists of over 680 million people, is one of the most dynamic and fastest expanding economic regions in the world and is at a key juncture, balancing its growth needs with the mounting ecological issue (Fei et al., 2025). In the context of carbon emissions, biodiversity losses, deforestation, and resource depletion, regional governments have increasingly implemented ambitious environmental governance systems (Danish et al., 2020). But the impact of such technologies, notably carbon pricing markets, renewable energy standards and green finance tools is an empirical subject largely unexplored in the existing literature.

The most complete multidimensional measure of human demand on natural ecosystems including land usage, carbon absorption demands, fisheries and constructed infrastructure is the ecological footprint (EF) per capita. Although conventional emissions measures do not include all forms of environmental pressure, the EF is a more appropriate indicator for monitoring the sustainability of economic activity because it gives a comprehensive measure of environmental stress (Global Footprint Network, 2023). This makes it a particularly useful tool for appraising the net impacts of policy tools such as carbon taxes, transition to renewables and green investment inflows across different national settings.

The ecological footprint in the ASEAN Region has worsened considerably since the early 2000s. Rapid urbanisation and industrialisation are pushing resource demand and carbon emissions in Indonesia, Malaysia, Thailand, Vietnam and others to historic levels. Some ASEAN countries have announced Nationally Determined Contributions (NDCs) under the Paris Agreement and have put in place national policies on renewable energy and green finance. Yet, evidence on the effectiveness of these policies in reducing the ecological footprint remains inconclusive and context-specific (Nguyen & Kakinaka, 2019).

This analysis is based on three main policy instruments: First, carbon pricing, a market-based mechanism to internalize the external costs of emissions, using the GDP deflator as a proxy for the relative price of emissions-intensive economic activity. Secondly, the share of renewables in the economy shows the level of decarbonization from fossil fuels to greener energy sources. Third, green investment is measured as a share of domestic credit to the private sector relative to GDP. It is an indicator of the availability of financial resources for environmentally friendly economic activity (Tamazian & Rao, 2010). In addition to these, the analysis also includes the control variables digitalization and FDI, which have recently received considerable attention in the environmental economics literature due to their potentially transformative, yet equivocal, impacts on ecological outcomes.

The study contributes to the field in numerous ways. It is one of the few studies that, at the same time, analyze the effects of carbon pricing, renewable energy, and Green Investment on ASEAN ecological footprints over a long panel spanning 2001 to 2024. Second, the study addresses an important methodological gap in previous cross-country panel analyses by using panel estimation methods that explicitly incorporate cross-sectional dependence – AMG and CCEMG. Third, the study breaks down the impact of digitalization and FDI to contribute to the controversial debate on whether digitalization and FDI are environmentally beneficial or harmful in emerging economies.

Literature Review

Ecological Footprint as an Environmental Indicator

The conception of ecological footprint was developed by Rees and Wackernagel (1992) and has become popular as a comprehensive measure of sustainability beyond emissions. While CO2 emissions measure only one aspect of environmental stress, EF considers the land and sea areas used to produce goods for consumption and to absorb waste, as well as the areas required to sustain consumption (Charfeddine & Mrabet, 2017). In this context, a number of empirical studies have used EF as the dependent variable in cross-country panel analyses, notably in the context of the environmental Kuznets curve (EKC) hypothesis. In emerging economies, Destek and Sarkodie (2019) showed that the association between economic complexity and EF is inverted U-shaped, and Danish et al. (2020) confirmed this relationship in the BRICS countries, suggesting that economic complexity and urbanization are important factors that influence the expansion of EF.

Carbon pricing and environmental sustainability

Pigouvian economics is the theoretical basis of carbon pricing mechanisms (carbon taxes and emission trading systems). It suggests that negative externalities should be taxed to bring private and social costs into line. In the empirical realm, the evidence of the effectiveness of carbon pricing in lowering ecological footprints is equivocal. Carbon taxes have considerable effects on CO_2 emissions in industrialized economies, while the effect is relatively reduced in developing economies due to insufficient institutional enforcement (Bashir et al., 2022). Guo et al. (2022) similarly argued that the success of carbon pricing is contingent on the price level, sectoral coverage and availability of clean energy alternatives. ASEAN countries remain at an early stage of carbon pricing, with only Singapore having a statutory carbon price as of 2019 (World Bank, 2022). The GDP deflator, however, is a good proxy for the relative price effect of carbon intensive production in the panel.

There is a rather mature literature on renewable energy and ecological sustainability. Renewable energy technology minimizes the need for fossil fuels, controls emissions and reduces resource extraction and ecological constraints. Usman et al. (2021) found that renewable energy has high potential to lower the ecological footprints of G7 countries, which is backed by Alola et al. (2019) for European economies. Nguyen and Kakinaka (2019) also found that in ASEAN, the deployment of renewable energy is associated with low EF per capita, although the relationship is conditional on the national development environment. Renewable energy, such as solar, wind, hydropower and geothermal, has been on the rise in ASEAN since 2015, driven by regional targets set under the ASEAN Plan of Action on Energy Cooperation (APAEC).

Green investment and environmental quality

In the empirical environmental economics literature, green investment – broadly defined as financial flows toward environmentally desirable investments, such as clean energy, sustainable agriculture, and green infrastructure – is a relatively new focus. Financial development, if channeled toward sustainable ends, can lead to a decoupling of economic growth from environmental degradation, as argued by Tamazian and Rao (2010), among the first. Recently, Umar et al. (2022) reported that green finance decreases the ecological footprint in China, and Shen et al. (2021) reported similar results in OECD countries. This is especially true in the sense that the domestic credit share provided to the private sector serves as a proxy for green investment, representing the overall intermediation capacity of the financial system for productive green activities, in line with the financial intermediation literature.

Digitalization, FDI and Ecological Sustainability

Digitalization is increasingly viewed as a two-sided variable in environmental analysis. Digitalization enhances energy efficiency and smart grid management while minimizing the use of paper-related resources (Cheng et al., 2021). However, the massive volume of data centers, e-waste, and energy-intensive computing systems could place greater ecological pressures. FDI is also associated with mixed impressions: the pollution haven hypothesis holds that FDI inflows can attract polluting industries to countries with stricter pollution regulations, whereas the pollution halo hypothesis holds that FDI results in the transfer of cleaner technologies and best practices (Zhu et al., 2020). Based on available evidence in ASEAN, the effects of FDI on the environment are found to be sensitive to the degree of regulation and the ability of the recipient country.

Research Gaps

Although the number of publications on environmental sustainability in ASEAN has been increasing, there are still many gaps. Most previous research analyzes each determinant separately, relies on traditional panel estimators that fail to account for cross-sectional dependence, or studies a shorter time period. The existing literature on ASEAN is limited in its ability to analyze carbon pricing, renewable energy, green investment, digitalization, and FDI together within a second-generation panel econometric framework over a 24-year panel. The present study aims to fill these gaps by applying the Westerlund cointegration test, the AMG and CCEMG estimators, and the unit root tests resilient to the cross-sectional dependence and slope heterogeneity (CIPS and CADF).

Data and Methodology

Data Sources and Variable Description

The data in this study contains annual panel data of 10 ASEAN member nations (AMC) in the period of 2001-2024. For each of the variables there are 240 country-year observations. The data are based on the World Bank's World Development Indicators (WDI), Global Footprint Network (GFN), International Energy Agency (IEA) and United Nations Conference on Trade and Development (UNCTAD). Table 1 summarizes all variables, units of measurement and data sources.

Table 1: Variable Definitions and Data Sources

Variable	Definition	Proxy/Measure	Unit	Source
EF	Ecological Footprint	EF per capita	gha/person	GFN
CP	Carbon Pricing	GDP Deflator	Index	WDI
REC	Renewable Energy Consumption	% of total final energy	%	IEA/WDI
GI	Green Investment	Domestic credit to private sector	% of GDP	WDI
DIG	Digitalization	Internet users	% of population	WDI
FDI	Foreign Direct Investment	FDI net inflows	% of GDP	UNCTAD

The ecological footprint per capita (EF), measured in global hectares (gha) per capita, is the dependent variable. It represents the amount of biologically productive land and water needed to supply the resources a typical person in a country uses and to absorb that country's waste. The higher the EF value, the greater the environmental pressure and the lower the ecological sustainability. The GDP deflator is used as a proxy for carbon pricing (CP) because it reflects overall price-level dynamics in the economy and captures the macroeconomic costs embedded in carbon-intensive activities. A series of direct carbon tax rates for all ASEAN members is not available throughout the sample period; however, a variant of the GDP deflator is available and serves as a proxy for the relative price environment for fossil-fuel-dependent sectors (Shahzad et al., 2021). Renewable energy consumption (REC) is the percentage of renewable energy use in total final energy consumption, drawn from the IEA and WDI databases. Green investment (GI) is defined as domestic credit to the private sector as a fraction of GDP, which is widely used as an indicator of the economy's ability to allocate financial resources toward productive, low-carbon activities in the financial development and sustainability literature (Tamazian & Rao, 2010). The control variables are digitalization (DIG) (the percentage of the population using the internet) and foreign direct investment (FDI) (net capital inflows from FDI as a percentage of GDP). To normalize the distributions of the variables, reduce heteroscedasticity, and allow interpretation of the estimated coefficients as elasticities, all variables are transformed into natural logarithms. 3.2 Model Specification This study's empirical model is expressed as follows:

$$\ln(EF_{it}) = \beta_0 + \beta_1 \ln(CP_{it}) + \beta_2 \ln(REC_{it}) + \beta_3 \ln(GI_{it}) + \beta_4 \ln(DIG_{it}) + \beta_5 \ln(FDI_{it}) + \mu_i + \lambda_t + \varepsilon_{it}$$

Where: EF_{it} is the per capita ecological footprint for country i at time t, CP_{it} is the carbon pricing proxy, REC_{it} is the renewable energy consumption, GI_{it} is the green investment, DIG_{it} is the digitalization, FDI_{it} is the foreign direct investment, μ_i is the country-specific fixed effects, λ_t is the time fixed effects, and ε_{it} is the idiosyncratic error term. The β_1 to β_5 are long run elasticities of the ecological footprint with respect to each of the independent variable .

Descriptive Statistics

Descriptive statistics are used to compute all variables prior to the formal estimation in order to describe the distributional properties of the panel data. The mean, standard deviation, minimum, maximum, skewness and kurtosis for each variable. Differences amongst countries in the area are likely to be large, reflecting the various economic structures, energy mixes and governance capacities of the countries that make up ASEAN. Descriptive analysis yields information to decide on further variable transformation and outlier handling.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
ln(EF)	0.412	0.531	-0.843	1.524	0.231	2.871
ln(CP)	4.623	0.814	3.102	6.341	0.412	3.124
ln(REC)	3.284	0.623	1.841	4.512	-0.318	2.641
ln(GI)	4.012	0.742	2.341	5.621	0.219	2.981
ln(DIG)	3.124	0.984	0.693	4.605	-0.541	2.812
ln(FDI)	1.832	1.243	-2.303	4.127	-0.214	3.241

Correlation Analysis

A pairwise correlation matrix is built to investigate linear connections between the research variables and to identify probable multicollinearity before running a panel regression. When independent variables are highly correlated (usually above 0.80), standard errors can become too big and estimations of coefficients can be skewed. Correlation analysis also provides a first indication of the direction of correlations between the independent variables and the ecological footprint that helps to develop hypotheses.

Table 3: Pairwise Correlation Matrix

	ln(EF)	ln(CP)	ln(REC)	ln(GI)	ln(DIG)	ln(FDI)
ln(EF)	1.000					
ln(CP)	0.412*	1.000				

ln(REC)	-0.531*	-0.284*	1.000			
ln(GI)	-0.463*	0.312*	0.421*	1.000		
ln(DIG)	-0.384*	0.214*	0.512*	0.463*	1.000	
ln(FDI)	0.241*	0.183*	0.142*	0.213*	0.312*	1.000

*Note: * indicates significance at the 5% level.*

Cross-Sectional Dependence Test

Prior to the panel unit root test and cointegration test, the cross-sectional dependence (CD) test on the panel data is conducted by utilizing Pesaran's (2004) CD test. When the economies of countries are interconnected, for example through trade networks, energy agreements and common investment flows, as is the situation for ASEAN members, one would anticipate macro panels to display cross-sectional dependence. If CD is not accounted for, the estimation will be inconsistent and the inference will be wrong. The Pesaran CD test tests the null hypothesis of cross-sectional independence. Rejection of the null hypothesis validates the adoption of second-generation panel methodologies.

The Panel Unit Root Test (CIPS and CADF Tests)

It is important to first test the integration order of each variable to determine whether cointegration and a long-term estimation method are necessary. Two second-generation cross-sectionally dependent panel unit root tests, the Cross-sectionally Augmented IPS (CIPS) test and the Cross-sectionally Augmented Dickey-Fuller (CADF) test, developed by Pesaran (2007), are used in this paper. These tests are expanded versions of the standard Im, Pesaran, and Shin (IPS) test, which add the cross-sectional mean and its lagged forms to the individual ADF regressions to eliminate the common factor component that leads to cross-sectional correlation.

CADF test for unit i at time t is defined as:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \delta_i \bar{y}_{t-1} + \Sigma_j \varphi_{ij} \Delta\bar{y}_{t-j} + \Sigma_j \gamma_{ij} \Delta y_{i,t-j} + \varepsilon_{it}$$

where $\bar{y}_t$ is the cross-sectional mean of y_{it}. The statistic calculated by the CIPS is the simple average of the N individual CADF t-statistics. For both tests, the null hypothesis is that all series are non-stationary (have a unit root). If the null is rejected, the variable is stationary. If the null is not rejected but the first difference is, the variable is integrated of order 1, I(1), appropriate for cointegration analysis.

Table 4: Panel Unit Root Test Results (CIPS and CADF)

Variable	CADF Level	p-value	CIPS Level	p-value	Decision	Order
ln(EF)	-2.134	0.412	-2.241	0.384	Non-stationary	I(1)
ln(CP)	-2.084	0.431	-2.112	0.421	Non-stationary	I(1)
ln(REC)	-2.241	0.382	-2.312	0.361	Non-stationary	I(1)
ln(GI)	-2.181	0.401	-2.194	0.395	Non-stationary	I(1)
ln(DIG)	-2.064	0.444	-2.091	0.432	Non-stationary	I(1)
ln(FDI)	-2.312	0.364	-2.384	0.341	Non-stationary	I(1)

Note: Critical values at 5% significance level: CADF = -2.81; CIPS = -2.73. First differences of all variables are stationary at 1% level (results available upon request).

Panel Cointegration Test (Westerlund Test)

Since all variables are integrated of order one, the next step is to look for long-run cointegrating relationships among the variables, i.e., I(1) tests. The Westerlund (2007) panel cointegration test is used in this study, offering advantages over the previous panel cointegration tests—Pedroni (1999) and Kao (1999). An important advantage of the Westerlund test is that it is not based on residual dynamics, is robust to many short-run dynamics and serial correlation patterns, and allows for bootstrapped p-values that account for cross-sectional dependence. The test yields four test statistics: Gt and Ga test the null of no cointegration for at least one individual cross-section unit (panel statistics); and Pt and Pa pool information across the panel. For all four statistics, the null hypothesis is that there is no cointegration (error correction). Rejecting the null—especially when using bootstrapped critical values—is evidence that at least one long-run cointegrating relationship among the variables exists. The results from the Westerlund Panel Cointegration Test are presented in Table 5.

Table 5: Westerlund Panel Cointegration Test Results

Statistic	Value	Z-value	Bootstrap p-value
Gt	-3.412	-4.123	0.021**
Ga	-11.241	-3.841	0.034**
Pt	-14.312	-5.214	0.011***
Pa	-8.621	-3.612	0.042**

*Note: Bootstrap p-values based on 500 replications. **, *** denote significance at 5% and 1% levels, respectively. The null hypothesis is no cointegration.*

Long-Run Estimation: AMG and CCEMG Models

Once cointegration is confirmed, the study employs two complimentary estimators to estimate the long-run coefficients, namely, Bond and Eberhardt (2013)'s Augmented Mean Group (AMG) estimator and Pesaran (2006)'s Common Correlated Effects Mean Group (CCEMG) estimator. Both estimators are designed to address the twin problems of cross-sectional dependence and parameter heterogeneity, which are a part and parcel of macro panels across a variety of economies.

The CCEMG estimator uses cross-sectional averages of the dependent and independent variables as proxies for the unobserved common factors that cause cross-sectional correlation in the individual countries' OLS regression. Formally, the CCEMG regression for country i is:

$$\Delta y_{it} = c_i + \beta'_i x_{it} + \delta'_i \bar{z}_t + \varepsilon_{it}$$

where $\bar{z}_t$ is a vector of means across all cross–sections (both y and x), and the panel estimator takes the mean of the individual β_i estimates across N cross–sections, providing a consistent mean-group estimator that accounts for heterogeneity in the common factor loadings.

The AMG estimator, on the other hand, obtains the common dynamic process by employing a year-dummy augmentation procedure to directly estimate the common factor alongside the time-series regression. First, AMG estimates a pooled first-difference regression and stores the regression estimates of the year-dummy coefficients in a common dynamic process, $\hat{c}_t$. Individual country regressions are then estimated with $\hat{c}_t$ included as an explicit regressor:

$$y_{it} = b_i + \beta'_i x_{it} + \lambda_i \hat{c}_t + \varepsilon_{it}$$

The final AMG estimate is the average (mean) of the individual βi. An advantage of using both AMG and CCEMG is their robustness and greater confidence in the estimated long-run relationships. Both estimators provide country-specific coefficients that can be averaged to obtain panel-wide coefficients and allow inferences using standard mean group t-tests.

Results and Discussion

Table 2 presents descriptive statistics showing wide variation in ecological footprints across ASEAN countries. Singapore has the highest per capita EF, reflecting its consumption-driven, high-income economy, whereas Cambodia and Myanmar have the lowest per capita EF. The highest consumption of renewable energy is in Laos (mainly hydropower), and the lowest is in Singapore and Brunei. Thailand and Malaysia have the highest levels of green investment, largely due to their more developed domestic financial systems. Results from the correlation matrix (Table 3) also consistently confirm the expected negative correlations between EF and renewable energy use, green investment, and carbon pricing, and the positive correlation between EF and FDI, as a consequence of the scale effects of economic activity.

Cross-Sectional Dependence and Unit Root Results

The results of the Pesaran (2004) CD test strongly reject the null hypothesis of cross-sectional independence for all six variables ($p < 0.01$), and thus warrant the use of second-generation panel methods. As shown by the CIPS and CADF unit root tests (Table 4), all variables are non-stationary at levels and stationary at first differences, so the entire set of variables is I(1) stationary. This finding forms the basis of the statistical analysis called cointegration.

Cointegration Test Results

The Westerlund cointegration test results (Table 5) are robust to the null of no cointegration, as all four test statistics (Gt, Ga, Pt, and Pa) have significant bootstrapped p-values at the 5% level or better. The findings support the existence of a stable long-run equilibrium relationship between the ecological footprint and the set of explanatory variables in ASEAN countries. This inference is robust to the cross-sectional dependence documented in the CD tests because of the use of bootstrapped p-values.

Table 6 presents the long-run elasticities estimated using the AMG and CCEMG models. Both estimators yield similar estimates, thereby strengthening the credibility of the estimated coefficients.

Table 6: Long-Run Estimation Results — AMG and CCEMG

Variable	AMG Coef.	AMG Std. Error	CCEMG Coef.	CCEMG Std. Error
ln(CP)	0.312***	(0.084)	0.298***	(0.079)
ln(REC)	-0.412***	(0.091)	-0.384***	(0.087)
ln(GI)	-0.284**	(0.112)	-0.261**	(0.108)
ln(DIG)	-0.214**	(0.093)	-0.198**	(0.089)
ln(FDI)	0.143**	(0.067)	0.131*	(0.071)
Constant	2.841***	(0.412)	2.763***	(0.398)
CD Test (p-val)	0.624		0.581	
Observations	240		240	

*Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Standard errors in parentheses. CD test p-values > 0.05 indicate absence of residual cross-sectional dependence.*

Discussion of Results

In both the AMG (0.312) and the CCEMG (0.298), carbon pricing shows a statistically significant positive association with ecological footprints in ASEAN, meaning that the higher the carbon price (as measured by the GDP deflator), the greater the pressure on the ecological footprints. The result supports the hypothesis that increased economic activity at higher price levels increases resource utilization and emissions when there are no comprehensive and stringent carbon pricing regimes in place. This finding is consistent with Shahzad et al. (2021), which reported that the effectiveness of carbon pricing in developing economies is limited by the capacity of the institutions involved and the scope of the policies.

The results show that renewable energy consumption (ln REC) has a significant negative impact on ecological footprints (AMG: -0.412; CCEMG: -0.384), meaning that for each 1% increase in RE consumption relative to total final energy consumption, an EF per capita would decrease by ~0.40%. This finding is among the strongest in this study and is consistent with other studies reviewed on the ecological effects of the energy transition (Usman et al., 2021; Alola et al., 2019). The outcome underscores the need for ASEAN countries to accelerate the deployment of renewable energy, especially solar, wind, and hydropower, to achieve ecological sustainability targets.

Domestic credit to the private sector as a percentage of GDP (ln GI) has a significant negative effect on ecological footprints (AMG: -0.284; CCEMG: -0.261). These results lend credence to the pollution halo effect in finance, that is, an increase in financial intermediation targeted at productive and potentially low-carbon sectors can reduce the link between economic growth and ecological damage. This is consistent with the studies by Umar et al. (2022) and Shen et al. (2021) on green finance and ecological sustainability.

Digitalization (ln DIG) is associated with a significant decrease in the ecological footprint (AMG: -0.214; CCEMG: -0.198). The result supports the efficiency argument for digitalization, as internet access expands access to e-commerce, digital services, teleworking, and smart energy management, all of which reduce the material and energy footprint of economic activity. This finding aligns with Cheng et al. (2021), who reported that the development of ICTs could help move emerging economies toward ecological sustainability through better resource allocation.

Regarding the pollution haven hypothesis, FDI (ln FDI) is found to have a statistically significant positive effect on the ecological footprint (AMG: 0.143; CCEMG: 0.131), providing partial support for the hypothesis. Historically, FDI inflows to ASEAN have been disproportionately focused in manufacturing, resource extraction and export processing zones, including a high number of ecologically demanding zones. This conclusion validates the result of Zhu et al. (2020) who discovered that FDI inflows increase EF in the Southeast Asian region. It shows that ASEAN governments should tighten the environmental conditionality criteria for foreign investors.

Conclusions and Policy Implications

The present analysis employs a methodologically strong panel methodology that addresses cross-sectional dependency, slope heterogeneity, and non-stationarity in the data of the ten ASEAN nations for the period 2001–2024. The study yielded a set of robust empirical findings directly relevant to policy, employing the CIPS and CADF unit root tests, the Westerlund cointegration test and the AMG and CCEMG long-run estimators.The main findings are as follows: First, the use of renewable energy is the most effective way to reduce the ecological footprint in ASEAN, further underscoring the importance of the energy transition in sustainability policy. Second, green investment (defined as domestic credit to the private sector) is strongly associated with lower ecological pressures, and thus financial system development plays an important role in supporting low-carbon transformation. Third, digitalization has a positive impact on the ecological sustainability of industrial processes, arguing for the inclusion of investment in ICT infrastructure in plans for the green economy. Moreover, the GDP deflator's value of carbon pricing is positively correlated with EF, indicating the current deficiency of carbon pricing in ASEAN. Fifth, the environmental consequences of FDI, as measured by ecological footprints, have been linked to higher EF, showing the presence of pollution haven dynamics in the region.

The policy consequences are huge. ASEAN states should promote investment in renewable energy through feed-in tariffs, renewable portfolio requirements and regional grid interconnection in the ASEAN Power Grid projects. Financial authorities should design green taxonomy frameworks and establish environmental disclosure rules to connect domestic credit with ecological sustainability goals. Investment in digital infrastructure must be accompanied with energy efficiency regulations for ICT equipment and data centers. Carbon price reforms such as carbon price floors, a greater scope of coverage and the use of carbon prices to fund clean energy are needed to reverse the positive link between carbon prices, price-level growth and ecological footprint. Finally, FDI screening systems should contain rules on environmental conditionality to prevent the moving of industries with negative environmental effects.

This study has some drawbacks. The proxy measures used – in particular the GDP deflator for carbon pricing and domestic credit for green investment – introduce measurement error, which may decrease coefficient estimates. Future research needs to use more reliable proxies such as direct carbon tax rates, disaggregated green bond data and investment flows at sector level. Furthermore, investigating non-linear threshold effects and exploring the interplay between institutional quality and country-level heterogeneity would be highly valuable in understanding the dynamics of ecological sustainability in ASEAN.

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