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# GREEN ECONOMICS IN ACTION: EXPLORING THE NEXUS BETWEEN INDUSTRIAL GROWTH, MARKET FORCES, AND CARBON CREDIT MOVEMENTS IN EMERGING ECONOMIES – WITH REFERENCE TO INDIA

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**Abstract**. This study examines the impact of key economic growth indicators on the carbon credit market in India, highlighting how selected macroeconomic variables shape its dynamics in an emerging economy. Using secondary data covering 11 years from the Reserve Bank of India (RBI) and BSE India, the research applies rigorous econometric methods, including the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit Root Tests, the Vector Error Correction Model (VECM), and Ordinary Least Squares (OLS) regression, to explore both short- and long-run relationships among variables. The analysis considers crude oil prices, automobile sales (AMS), the Housing Price Index (HPI), GDP, the Index of Industrial Production (IIP), and the Green Exchange Index—an indicator of sustainable finance performance and investor confidence in carbon markets. These variables capture economic activity, market sentiment, and energy dependence, all of which influence carbon credit pricing and demand. Empirical results indicate that crude oil prices and AMS negatively affect carbon credits, whereas HPI, GDP, and IIP positively impact them. The Wald test indicates no long-run relationship between carbon credits and crude oil, AMS, or HPI. However, GDP, IIP, and the Green Exchange Index significantly boost carbon credits in the short run. A robustness check using 2024 data confirms the consistency and structural stability of these associations over time. The study concludes that macroeconomic and industrial indicators are decisive in shaping carbon credit movements. Strengthening industrial productivity, promoting sustainable finance, and aligning macroeconomic management with green policy objectives can enhance the efficiency of carbon markets. These findings provide valuable insights for policymakers, investors, and environmental economists seeking to harmonise economic growth with emission reduction goals. The Indian experience also offers a strategic reference for other emerging economies pursuing sustainable carbon trading frameworks.

**Keywords***:* Carbon Credits, Economic Growth, GDP, VECM, Climate Policy, India.

**JEL Classification:** O44, Q55, Q56

## 1. INTRODUCTION

Economic growth refers to the growth of our economy. It studies the relationship of carbon credits, which affect our economy, and the carbon credit permits that allow the owner to emit a certain amount of carbon dioxide or other greenhouse gases. Economic growth is an increase in the production of economic goods and services. The issue of climate change is a major global challenge facing humanity today, and the increasing carbon emissions have led to the frequent occurrence of sea level rise, increased drought periods, and reduced agricultural yields, so the promotion of low-carbon development has become one of the urgent issues for humanity (Souvik Bhattacharjya, 2024). If the Chinese government does not take measures to reduce carbon emissions, China's emissions will continue to grow, causing irreversible damage to the entire ecosystem. Similarly, as a responsible country, the Chinese government has been actively addressing carbon dioxide emissions to promote green, low-carbon cycle development. Meanwhile, the benchmarking rule and the grandfather rule in the initial allocation mode of carbon quotas have been compared, and the impact mechanism of the CT system on industries has been constructed by constructing a theoretical framework. The existing research mainly analyses and demonstrates the CT market mechanism two and its impacts on energy, the environment, and economic development. However, 3E is a coordinated development system, and there are few studies in the literature on the impact of the CT market mechanism on the 3E system as a whole. The development of the economy provides labour for production and a living for the energy subsystem. It promotes the development of the environmental protection industry for the ecological subsystem. Energy is the foundation of equipment development and technical development. Carbon credits are a market-based approach to reducing greenhouse gas emissions. They work by assigning a monetary value to each tonne of carbon dioxide (or equivalent greenhouse gas) that is not emitted into the atmosphere. This value can then be traded on a carbon market, with businesses and governments buying credits to offset their own emissions. Carbon credits can have both positive and negative impacts on economic growth, depending on how they are implemented and the context in which they are used (Newell and Pizer, 2013; Streck and Lin, 2008).

The variables selected for this analysis are fundamentally linked to market sentiment, industrial productivity, and energy utilisation patterns. Oil prices reflect energy costs that directly influence emissions, while automobile sales reflect transportation demand. The housing price index captures real estate dynamics and construction-related energy consumption, and GDP measures overall economic performance. The Industrial Index of Production (IIP) indicates manufacturing activity levels, while the green exchange index reflects investor confidence in sustainable financing and carbon markets. This framework ensures that variable selection is anchored in both economic and environmental relevance, consistent with established international research (Alharbi et al., 2023; Belgacem and Khatoon, 2023).

However, there is still a lack of literature on the Indian context, where carbon credit markets are in the development phase and face specific economic and policy issues. This study fills that gap by connecting macroeconomic factors to carbon credit performance, using both short- and long-term evidence from economic analysis. Accordingly, the goals of the study are twofold: (1) to examine the effects of specific economic determinants on carbon credit trends in India, and (2) to analyse how these determinants collectively influence carbon markets' operations and their potential contribution to making economic development compatible with environmental sustainability.

## 2. THEORETICAL BACKGROUND

**Financial actors' part in India's carbon markets.**

Singh et al. (2024) highlight how the inclusion of financial players can lead to increased price volatility, bubble formation, and market manipulation. The research stated that the growth of strong carbon markets depends on economic actors. To prevent unforeseen repercussions, their integration must be appropriately timed and controlled. Together, global experience, the growth of the derivatives market, and India's previous policy instruments provide a valuable basis for shaping the future structure of the carbon market.

**Indian viewpoints on market development and policy.**

Souvik Bhattacharjya (2024) **e**xamined the Indian Green Credit Program and its potential to drive the country's energy transition and circular bioeconomy. The research highlighted the need to align environmental goals with economic growth and was placed within the Indian policy context. It was demonstrated that there may be two benefits to aligning credits with ecosystem services. The research suggested that robust verification processes should be included in future designs.

The Centre examined the impending carbon market in India and identified the obstacles and possible solutions for its successful implementation. The paper offered a framework for policy review with an emphasis on India. It discovered weaknesses in the regulatory framework and institutional preparedness. The study suggested that stakeholder interaction and decentralised governance be included in future procedures.

Chaturvedi et al. (2024) investigated how some selected climate policies influenced India's emission trajectories. The research was conducted using national-level modelling techniques. It was found that consistent policy enforcement greatly helps to reduce emissions. The authors find that sector-specific emissions should be prioritised in future policy.

Ding et al. (2025) conducted a subnational study of coal plant retrofits in India to evaluate their contribution to the development of a net-zero electricity system. The data-driven study highlighted regional differences and found that planned retrofitting could significantly reduce emissions. They recommended that future retrofit plans incorporate renewable energy.

Malik et al. (2024) evaluated how implementing an emissions trading program might affect India's net-zero goals. Indian economic and emission data were used in the modelling-based evaluation. According to the study, an ETS, when combined with strict regulatory controls, may successfully reduce emissions. Plans must be revised to account for the region's industrial diversity.

Mundol and Mukherjee (2024) published an opinion piece examining the requirements for a robust carbon market in India. Drawing from current policy drafts, the article stressed the importance of early-stage efficiency. The outcome emphasised the need for clear rules, accountability, and integration with global standards. The analysis recommended that future policies should aim for adaptive frameworks.

Paul (2018) evaluated the paper and explored an overview of carbon credit and carbon trading in India. The adoption of the Kyoto Protocol (KP) on February 16, 2005, has sparked worldwide awareness of the need to reduce Greenhouse Gas (GHG) emissions. Since then, almost all the industrially developed and developing countries throughout the world have begun to take this issue seriously and have engaged in formulating carbon-emission standards and guidelines to control these harmful gas emissions. Being a developing country, India was not an exception and hence joined the race. Accordingly, the concepts of carbon credits and carbon trading have emerged from their efforts and are now accepted worldwide as a sustainable solution. The solution to the problem is concerned within a very short time span since its emergence. Therefore, this paper aims to sketch the current landscape of carbon credits and carbon trading in India and identify their prospects.

Boutabba (2014) examines the long-run equilibrium and the existence and direction of causal relationships among carbon emissions, financial development, economic growth, energy consumption, and trade openness for India. Our main contribution to the literature on Indian studies lies in investigating the causes of carbon emissions by accounting for the role of financial development and using single-country data. The results suggest evidence of long-run and causal relationships among carbon emissions, financial development, income, energy use, and trade openness. Economic growth has a long-run positive impact on carbon emissions, suggesting that it reduces environmental degradation. Moreover, the Granger causality test indicates a long-run unidirectional causality running from financial development to carbon emissions and energy use.

**Global views of the macroeconomic reasons for carbon markets.**

Indian research has primarily concentrated on regulatory frameworks, policy formulation, and sector-specific case studies, whereas international studies have focused more on macroeconomic factors, pricing movements, and systemic relationships. Demonstrating how India's experience connects to global trends through this transition is essential.

Numerous international research studies have also shown that macroeconomic factors influence carbon credit markets beyond India. Santos et al. (2023) utilised Brazil's carbon credit system to show that credit prices and trading volumes are directly influenced by GDP growth, industrial production, and fluctuations in energy prices. Maseko and Moyo (2022) discovered significant links among fuel price fluctuations, economic outcomes, and credit demand in their analysis of South Africa's carbon tax and offset program.

Studies of developing economies such as Brazil and South Africa elucidate the strong influence of GDP and energy prices on carbon credit markets, despite the pressures observed in India (Matenda et al.).

**China's economic expansion goals and trade-offs for emissions.**

Papers by Abbasi et al. (2022), ADB et al. (2022), and Ben-Salha et al. (2022) investigated the effect of monetary development on fossil fuel byproducts, using 30 standard panel data sets from China from 2003 to 2019. The review showed that, with proper consideration of endogeneity and strength, financial development targets are positively associated with fossil fuel byproducts. Heterogeneity investigation shows that, first and foremost, the increment of monetary development focuses in eastern, central and western districts advances fossil fuel byproducts. The effect of monetary development on fossil fuel byproducts is higher in eastern locales than in central and western areas. Carbon emissions pose a new threat to sustainable development in China, and local government actions can play an essential role in energy conservation and emissions reduction. This paper explores the theoretical mechanisms and pathways through which economic growth targets affect carbon emissions. It conducts an empirical analysis using 30 provincial panel datasets from China from 2003 to 2019.

Chen et al. (2022) evaluated the paper and proposed that far-reaching carbon execution be assessed holistically. In light of the insights from the effectiveness examination writing, this paper proposed a new methodology: estimating the carbon efficiency of an economy using a complete variable DEA-based model. This paper then introduced an exact review utilising information gathered from PRC territories, independent locales, and districts in 2005. The most commonly used measure of an economy's carbon performance is carbon intensity (carbon dioxide per gross domestic product [CO/GDP]). As an indicator, it is easy to understand and use, but it has severe limitations.

Carbon sequestration is a significant market tool for driving development and reducing carbon dioxide emissions in industrial areas in China. Zhao et al. (2022) studied a paper. They evaluated the effects of carbon exchanging on financial results and the decrease in carbon dioxide emanations decrease in China's modern areas by utilizing the information envelopment examination (DEA) based advancement models, in view of three carbon exchanging plans, i.e., no exchanging (NT), sectoral exchanging (ST), and sectoral-and worldly exchanging (STT) during 2006-2015. Carbon trading is an important market tool for driving growth and reducing carbon dioxide emissions in China's industrial sectors. This paper assesses the impacts of carbon trading on economic output and carbon dioxide emissions reduction in China’s industrial sectors by employing data envelopment analysis (DEA)- based optimisation models under three carbon trading schemes.

While looking at Chinese studies highlights tensions between emissions control and economic growth targets, showing that rapid expansion without strict policies might result in higher carbon emissions (Cai et al. (2024); Mehmood et al. (2024)).

The full effect of outbreaks, including how long the emergency will last and how energy utilisation and related CO2 emissions will be affected, is unclear. This survey aims to guide policymakers and legislators in countries toward a superior course by providing a comprehensive and persuasive overview of the pandemic's significant effects on the world economy, global energy markets, and energy-related CO2 emissions that may arise in the coming years. To be sure, considering that quick response is expected with equal earnestness to address three things: the pandemic, the economic slump, and the environmental emergency. This study frames strategy ideas that can be utilised during these uncertain times as an aide.

Furthermore, numerous international studies provide evidence of the macroeconomic factors influencing carbon credit markets. Energy prices, industrial output, and business-cycle dynamics all directly affect carbon allowance prices, according to research on the European Union Emissions Trading

System. While states continue to experience economic expansion, research on the Regional Greenhouse Gas Initiative (RGGI) in North America shows that energy costs and GDP growth drive demand for allowances (Bertrand, 2012; Murray and Maniloff, 2015; Nyonho et al., 2023). Evidence from Japan and Korea shows how trade openness and industrial activity influence the performance of carbon credits Silva and Vieira, 2025). Research from Brazil also demonstrates that changes in energy prices and GDP growth have a direct impact on credit availability and market expansion Benevit et al., 2023). The effects of policy changes were significantly amplified by speculative pressures, according to this econometric study, which examines the notable rise in EU carbon permit prices after the 2018 revisions (Friedrich et al., 2019).

Using econometric matching techniques and analysing German manufacturing enterprises, this study shows that companies subject to EU ETS restrictions reduce emissions by a considerable amount, without suffering appreciable drops in output or competitiveness. This proves that macro-level regulations can decrease firm-level emissions without impairing economic performance Löschel et al., 2019).

The study by Berrisch et al. (2023) simulated the unpredictable, interconnected characteristics of the European energy and carbon markets, particularly during geopolitical emergencies (e.g., fluctuations in energy prices). The findings illustrated how macroeconomic energy trends affected carbon markets, showing that carbon prices fluctuated alongside those of oil, gas, and electricity markets.

According to research from the US, EU, Japan, and Korea, carbon credit prices in developed markets are sensitive to industrial output, energy prices, and policy, with financial speculation amplifying these effects Du et al., 2025).

In conclusion, the literature review reveals that a complex interplay of macroeconomic variables, including GDP, industrial output, energy pricing, and regulatory policies, shapes carbon credit markets. International evidence from carbon markets such as the EU ETS, RGGI, and systems in China, Korea, Japan, Brazil, and South Africa demonstrates that macroeconomic conditions consistently drive both demand fluctuations and pricing dynamics for carbon allowances. While extensive research in India has focused on regulatory structures, climate policy frameworks, and market mechanisms, there remains insufficient investigation using economic models that capture both immediate and long-term temporal relationships to analyse India's carbon credit market systematically. This study aims to fill this research gap by examining how economic growth indicators affect carbon credit performance in India, while drawing on policy insights from international carbon markets.

## 3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

### 3.1 Research Objective

- To know the relation of select Economic indicators with carbon credits.
- To identify the impact of select Economic Indicators on carbon credits.

### 3.2 Research Methods

This study uses secondary time-series data and a quantitative research design to examine how economic growth indicators affect the Indian carbon credit market. The Reserve Bank of India (RBI) and BSE India are two trustworthy, publicly available databases from which the data was gathered. The data covers 11 years, from 2011 to 2022.

The decline in the clean development mechanism (CDM) market during the KYOTO protocol era and the subsequent shift to the Paris Agreement, along with Indian domestic carbon policies, are evident in the selected timeframe (2011–2022). As a result, this timeframe is perfect for examining structural changes in carbon credits. While BSE India offers market-focused indices like Carbonex and Greenex that reflect the financial aspects of the carbon market, RBI is chosen for its delivery of reliable macroeconomic metrics such as GDP, IIP, and the Housing Index.

To provide a robust examination of the dynamic relationships between the selected macroeconomic variables and carbon credit indices, the methodology systematically applies econometric methods. Using Carbonex as a proxy for carbon credits, the study examines how it relates to key environmental and economic factors.

### 3.3 Data Description and Variable Selection

Dependent Variable:

Carbonex: A market-based carbon credit index that gauges how well ecologically conscious businesses are performing.

Independent Variable:

The degree of industrial activity is reflected in the IIP (Index of Industrial Production).

Electricity Generation: Shows patterns in energy use.

Greenex: A BSE green index that gauges business performance with an emphasis on sustainability.

Automobile Sales: A stand-in for industries tied to emissions and customer demand.

One precise measure of environmental performance is carbon emissions.

Macroeconomic indicators such as GDP, exports, and foreign reserves are used to evaluate the external sector dynamics and the overall health of the economy.

### 3.4 Justification for Variable Selection

In both global and Indian sources, the variables selected for this study were chosen for their documented relevance to energy consumption, industrial output, and market mood. Crude oil prices are a major contributor to energy costs and have apparent effects on greenhouse gas emissions, but they can also influence business-level decisions about purchasing carbon credits. Liu et al.(2023); Wei et al.(2023). An essential source of carbon emissions in India is transportation-related emissions, which are addressed via automobile sales (AMS). Hagemann et al (2020). The confidence of homeowners and investors is reflected in the Housing Price Index (HPI), which can influence demand for sustainable development initiatives and green infrastructure. Energy consumption and emissions are influenced by macroeconomic and industrial activity, as measured by GDP (gross domestic product) and IIP (index of industrial production). Fuinhas et al.(2025); Mironiuc et al.(2021); Principles (2011); Tiwari et al.(2025). The green exchange index, a proxy for the success of environmentally conscious businesses, is expected to correlate positively with the performance of the carbon credit market. (2025); Barakat et al. (2023); Y. Li and Lin (2024); Malik et al. (2024); Zhao et al. (2023) have identified the same characteristics as predictors of carbon market dynamics, which lends credence to this methodology.

### 3.5 Unit Root Testing for Stationarity

To ensure the validity of the time series analysis, it is essential to check whether the variables are stationary. A series is said to be stationary if its variance and mean, among other statistical characteristics, don't change over time. Spurious regression refers to deceptive regression findings that non-stationary data can produce.

The following tests were applied:

Augmented Dickey-Fuller (ADF) Test

Phillips-Perron (PP) Test

These tests help determine the order of integration of each variable (I(0) or I(1)) and guide the appropriate choice of models for subsequent analysis. Employing both ADF and PP ensures robustness, as ADF addresses serial correlation in the error terms, whereas PP is more flexible in handling heteroskedasticity and autocorrelation.

### 3.6 Vector Error Correction Model (VECM) and Cointegration

A Vector Error Correction Model (VECM) is suitable if it is determined that the variables are cointegrated, integrated of order one, and I(1). To preserve long-term equilibrium among the variables, this model not only accounts for short-term deviations but also considers them. The VECM assesses whether certain independent factors, including IIP, power generation, Greenex, auto sales, and carbon emissions, have a significant long-term impact on carbon credits (Carbonex). The dependent variable's rate of adjustment to return to equilibrium following a shock is indicated by the error correction term (ECT). VECM was selected over simple variables because it accounts for both short-term adjustments and long-term equilibrium relationships, which are essential in policy-driven carbon markets susceptible to shocks.

### 3.7 Robustness of the study

The research utilised, along with the VECM model, to ensure the reliability of the findings. To assess the immediate reaction of macro variables to variations in carbon credits, standard OLS regressions were conducted as a reference. This dual method allowed for consistency tests between the more complex structural model estimates and the simpler regression estimates.

Wald tests, unlike simple statistical correlations, were used in the study to determine whether variables had genuine long-term causal relationships. The research re-evaluated the model and broadened the dataset to include 2024 data to validate robustness. The coefficients showed minimal variation, indicating that the results were consistently stable over time and were independent of the specific period. The dependent variable was switched from CARBONEX to GREENEX to perform another sensitivity analysis. The direction of the correlations remained stable, showing that the results were unaffected by the chosen individual variable specification and model setup.

The overall conclusions were supported by these robustness evaluations, which confirmed that the research outcomes reflect genuine relationships rather than statistical anomalies.

## 4. RESULTS AND DISCUSSION

### 4.1 Objective 1: To examine the relationship between selected economic indicators and carbon credits

*Tab.1*

*Results of Selected Macroeconomic Variables relevant to carbon credit market analysis*

| Variables | Level | | 1st diff | | 2nd diff | |
|---|---|---|---|---|---|---|
| | t-statistics | prob.* | t-statistics | prob.* | t-statistics | prob.* |
| crude oil | - | - | -3.476 | 0.0201 | - | - |
| automobile sales | - | - | -2.9774 | 0.0544 | - | - |
| Housing Pride Index | - | - | -4.55776 | 0.002 | - | - |
| GDP | - | - | -4.60588 | 0.0018 | - | - |
| IIP | - | - | -5.18641 | 0.0005 | - | - |
| carbon credits | - | - | -5.31244 | 0.0004 | - | - |

*Source: Reserve Bank of India; BSE; Researchers' Calculation*

Carbon credits vs. crude oil, automobile sales, and Housing price index.

Table 1 above presents the unit root test used to assess the significance of the collected data. To know the importance of the data, the probability value of the test mentioned above should be less than 0.05. The results indicate that the probability values for carbon 22 credits vs crude oil, housing pride index, GDP, and IIP are less than 0.05. For carbon credits vs. automobile sales value, the p-value is 0.05.

1st step Leg Length criteria.

*Tab.2*

*VAR Lag Order Selection Criteria for Carbon Credits, Crude Oil, AMS, and HPI*

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | -261.4617 | NA* | 3972844* | 26.54617* | 26.74531* | 26.58504* |
| 1 | -252.6830 | 13.16803 | 8538474 | 27.26830 | 28.26403 | 27.46268 |

**Note: * indicates lag order selected by the criterion*

LR: sequential modified LR test statistic (each test at 5% level).
FPE: Final prediction error.
AIC: Akaike information criterion.
SC: Schwarz information criterion.
HQ: Hannan-Quinn information criterion.
Source: Reserve Bank of India; BSE; Researchers' Calculation.

Table 2 presents the lag-order selection criteria for the model. The results indicate that the LR test and the final prediction error seem to fit at lag 0. And criteria such as AIC, SC, and HQ are also observed to be fit at lag 0. Hence, the model indicates that lag 0 is optimal, but lag zero does not have any valid estimates. The study will, by default, consider lag one as the optimal lag for estimating the VECM.

*Tab.3*

*Vector Error Correction Estimates for Carbon Credits and Key Economic Indicators (Model 1)*

| **Vector Error Correction Estimates** | | | | |
|---|---|---|---|---|
| **Standard errors appear in ( ) & t-statistics appear in [ ]** | | | | |
| Cointegrating Eq: | CointEq1 | Coefficient | Standard Error | t-Statistic |
| DCAR_CRD(-1) | 1.000000 | | | |
| DC_OIL(-1) | 157.2521 | | | |
| | (20.9894) | | | |
| | [ 7.49199] | | | |
| DAMS(-1) | 30.29290 | | | |
| | (15.7165) | | | |
| | [1.92746] | | | |
| DHPI(-1) | 24.30289 | | | |
| | (8.10237) | | | |
| | [2.99948] | | | |
| C | -168.8900 | | | |
| Error Correction: | D(DCAR_CRD) | D(DC_OIL) | D(DAM) | D(DHPI) |
| CointEq1 | -0.489771 | -0.005311 | -0.000101 | -0.018359 |
| | (0.35047) | (0.00099) | (0.00224) | (0.00241) |
| | [-1.39747] | [-5.37013] | [-0.04496] | [-7.63143] |
| D(DCAR_CRD(1)) | -0.369129 | 0.003386 | -0.000592 | 0.011740 |
| | (0.27660) | (0.00078) | (0.00177) | (0.00190) |
| | [-1.33454] | [ 4.33893] | [-0.33465] | [ 6.18342] |
| D(DC_OIL(-1)) | 114.2604 | -0.281451 | -0.440660 | 0.649616 |

| | | | | |
|---|---|---|---|---|
| | (72.1273) | (0.20352) | (0.46102) | (0.49510) |
| | [ 1.58415] | [-1.38294] | [-0.95584] | [ 1.31210] |
| D(DAMS(-1)) | -3.592056 | 0.272494 | -0.057293 | 1.431451 |
| | (44.9834) | (0.12693) | (0.28752) | (0.30877) |
| | [-0.07985] | [2.14686] | [-0.19927] | [ 4.63591] |
| D(DHPI(-1)) | 3.546212 | 0.131979 | 0.179341 | -0.088420 |
| | (21.5729) | (0.06087) | (0.13789) | (0.14808) |
| | [0.16438] | [2.16819] | [1.30064] | [-0.59711] |
| C | 31.34625 | -0.155644 | -0.102312 | 0.267576 |
| | (79.0083) | (0.22293) | (0.50500) | (0.54233) |
| | [ 0.39675] | [-0.69817] | [-0.20260] | [ 0.49338] |
| R-squared | 0.613197 | 0.781932 | 0.150565 | 0.873521 |
| Adj. R-squared | 0.464427 | 0.698060 | -0.176141 | 0.824875 |
| Sum sq. resids | 1506234. | 11.99208 | 61.53554 | 70.96945 |
| S.E. equation | 340.3882 | 0.960452 | 2.175661 | 2.336491 |
| F-statistic | 4.121767 | 9.322897 | 0.460857 | 17.95674 |
| Log likelihood | -134.1263 | -22.58801 | -38.12400 | -39.47903 |
| Akaike AIC | 14.75014 | 3.009264 | 4.644632 | 4.787266 |
| Schwarz SC | 15.04838 | 3.307508 | 4.942876 | 5.085510 |
| Mean dependent | 12.52716 | -0.095368 | -0.075263 | 0.235316 |
| S.D. dependent | 465.1199 | 1.747895 | 2.006142 | 5.583286 |
| Determinant residual covariance (dof adj.) | | 1673443. | | |
| Determinant resid covariance | | 366749.9 | | |
| Log likelihood | | -229.5575 | | |
| Akaike information criterion | | 27.11131 | | |
| Schwarz criterion | | 28.50312 | | |
| Number of coefficients | | 28 | | |

*Source: Reserve Bank of India; BSE; Researchers' Calculation*

Table 3 depicts the VECM of economic growth and carbon credits. Here, carbon credits are treated as dependent variables, while economic factors such as crude oil, AMS, and HPI are treated as independent variables. The coefficient value for crude oil on carbon credits is -0.6981; the coefficient value for carbon credits on AMS is -0.2026; and the coefficient value for carbon credits on HPI is 0.04933. It indicates that economic factors, such as crude oil and AMS, have a negative impact, while factors such as HPI have a positive effect.

System Equation.

D(DCAR_CRD) = C(1)*( DCAR_CRD(-1) + 157.252106369*DC_OIL(-1) + 30.2929047709*DAMS(-1) + 24.3028876119*DHPI(-1) – 168.890046898) + C(2)*D(DCAR_CRD(-1)) + C(3)*D(DC_OIL(-1)) + C(4)*D(DAMS(-1)) + C(5)*D(DHPI(- 1)) + C(6)

C(1)=c(2)=0

3rd step – Wald test.

Walt test with respect to CRUDE OIL, AMS, HPI. The following is the hypothesis.

Null hypothesis: there is no long-run relationship between Carbon credits and CRUDE OIL, AMS, and HPI.

Alternative hypothesis: a long-run relationship exists among Carbon credits, CRUDE OIL, AMS, and HPI.

*Tab.4*

*Wald Test Results for Long-Run Relationship Between Carbon Credits, Crude Oil, AMS, and HPI*

| Wald Test: | Test Statistic | df | Probability |
|---|---|---|---|
| System: %system | | | |
| Test Statistic | Value | df | Probabilty |
| Chi-square | 13.59476 | 2 | 0.0011 |
| Null Hypothesis: C(1)=C(2)=0 | | | |
| Null Hypothesis Summary: | | | |
| Normalized Restriction (= 0) | | Value | Std. Err. |
| C(1) | | -0.489771 | 0.350470 |
| C(2) | | -0.369129 | 0.276596 |
| Restrictions are linear in coefficients. | | | |

*Source: Reserve Bank of India; BSE; Researchers' Calculation*

Table 4 illustrates the Wald test results for the impact of carbon credits on crude oil, AMS, and HPI. From the chi-square test, the calculated value for carbon credits on crude oil, AMS, and HPI is 13.5947, which exceeds the critical value. As the p-value is greater than 0.05, the null hypothesis is accepted, and the alternative hypothesis is rejected, i.e., there is no long-run relationship between the impact of carbon credits and crude oil, AMS, and HPI.

Carbon credits vs GDP, IIP

1st step – lag length criteria

VAR Lag Order Selection Criteria

Endogenous variables: DCAR_CRD, DGDP, DIIP Exogenous variables: C

Lag LogL LR FPE AIC SC HQ

0 -323.9437 NA 3.17e+10 32.69437 32.84373 32.72353

1 -308.2628 25.08950* 1.65e+10* 32.02628* 32.62372* 32.14291*

*indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level) FPE: Final prediction error

AIC: Akaike information criterion SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

The data above represent the lag-order selection criteria for the model. The result indicates that the LR test and the final prediction error are well fit at lag 0. And criteria such as AIC, SC, and HQ are also observed to be fit at lag 0. Hence, the model indicates that lag 0 is optimal, but lag zero does not have any valid estimates. The study will, by default, consider lag one as the optimal lag for estimating the VECM.

*Tab. 5*

*Vector Error Correction Model Estimates for Carbon Credits, GDP, and IIP (Model 2)*

| Vector Error | Correction Estimates | Coefficient | Std. Error | t-Statistic |
|---|---|---|---|---|
| Standard errors in ( ) | t-statistics in [ ] | | | |
| Cointegrating Eq | CointEq1 | | | |
| DCAR_CRD(-1) | 1.000000 | | | |

| | | | | |
|---|---|---|---|---|
| DGDP(-1) | -22.11594 | (10.3988) | [-2.12677] | |
| DIIP(-1) | -16.21670 | (7.87650) | [-2.05888] | |
| C | -181.5989 | | | |
| Error Correction: | D(DCAR_CRD) | D(DGDP) | D(DIIP) | |
| CointEq1 | -0.241981 | 1.67E-05 | -5.11E-06 | |
| | (0.08918) | (0.00019) | (0.00013) | |
| | [-2.71380] | [0.08740] | [-0.03786] | |
| D(DCAR_CRD(-1)) | -0.146446 | -0.00064 | -0.000184 | |
| | (0.21079) | (0.00046) | (0.00032) | |
| | [-0.69470] | [-1.39445] | [-0.57342] | |
| D(DGDP(-1)) | -3.815311 | 0.354217 | 0.212885 | |
| | (11.3983) | (0.02516) | (0.01753) | |
| | [-0.33471] | [14.0709] | [12.1426] | |
| D(DIIP(-1)) | -18.92521 | -0.005508 | 0.160154 | |
| | (10.9949) | (0.02428) | (0.01691) | |
| | [-1.72368] | [-0.22677] | [9.47016] | |
| C | -16.62186 | 0.013012 | 0.008515 | |
| | (18.0017) | (0.03972) | (0.02767) | |
| | [-0.92348] | [0.32757] | [0.30778] | |
| R-squared | 0.481888 | 0.969021 | 0.985014 | |
| Adj. R-squared | 0.317618 | 0.957964 | 0.980286 | |
| Sum sq. resids | 1720210. | 8.679893 | 4.248935 | |
| S.E. equation | 301.1724 | 0.664781 | 0.463019 | |
| F-statistic | 2.934466 | 88.05025 | 206.5697 | |
| Log likelihood | -132.8546 | -15.32735 | -9.686388 | |
| Akaike AIC | 14.82785 | 1.929194 | 1.440672 | |
| Schwarz SC | 15.12609 | 2.227438 | 1.738916 | |
| Mean dependent | 21.13871 | 0.102199 | 0.063897 | |
| S.D. dependent | 364.5704 | 3.290923 | 3.302843 | |
| Determinant residual covariance (dof adj.) | 2719141. | | | |
| Determinant residual covariance | 1556325. | | | |
| Log likelihood | -155.3091 | | | |
| Akaike information criterion | 17.40096 | | | |
| Schwarz criterion | 18.59419 | | | |
| Number of coefficients | 18 | | | |

*Source: Reserve Bank of India; BSE; Researchers' Calculation*

Table 5 depicts the VECM of economic growth and carbon credits. Here, carbon credits are treated as dependent variables, while economic factors such as GDP and IIP are treated as independent variables. The coefficient value of GDP on carbon credits is 0.0960, and the coefficient value of carbon credits on IIP is 0.0744. This suggests that economic factors such as GDP and IIP have a positive impact.

D(DCAR_CRD) = C(1)*( DCAR_CRD(-1) – 22.1159221384*DGDP(-1) – 16.2167401733*DIIP(-1) – 181.598939694 ) + C(2)*D(DCAR_CRD(-1)) + C(3)*D(DGDP(-1)) + C(4)*D(DIIP(-1)) + C(5)

3rd step – Wald test

Walt test with respect to GDP, IIP

The following is the hypothesis

Null hypothesis: there is no long-run relationship between the carbon credits impact and GDP, IIP.

Alternative hypothesis: a long-run relationship exists between the impact of carbon credits and GDP and IIP.

*Tab.6*

*Wald Test Results for Long-Run Relationship Between Carbon Credits, GDP, and IIP*

| Wald Test: | Test Statistic | Value | Probability |
|---|---|---|---|
| System: %system | | | |
| Test Statistic | Value | df | Probability |
| Chi-square | 13.59476 | 2 | 0.0011 |
| Null Hypothesis: C(1)=C(2)=0 | | | |
| Null Hypothesis Summary: | | | |
| Normalized Restriction (= 0) | | Value | Std. Err. |
| C(1) | | -0.489771 | 0.350470 |
| C(2) | | -0.369129 | 0.276596 |
| Equations are linear in coefficients. | | | |

*Source: Reserve Bank of India; BSE; Researchers' Calculation*

Table 6 illustrates the Wald test results for the impact of carbon credits on crude oil, AMS, and HPI. From the chi-square test, the calculated value for carbon credits on crude oil, AMS, and HPI is 13.5947, which exceeds the critical value. As the p-value is greater than 0.05, the null hypothesis is accepted, and the alternative hypothesis is rejected, i.e., there is no long-run relationship between the impact of carbon credits and crude oil, AMS, and HPI.

### 4.2. Objective 2: To identify the impact of select Economic Indicators on carbon credits

This objective sought to assess the impact of selected economic indicators on carbon credits over 20 years. For this, the study used the Ordinary Least Squares method to identify the effects of selected economic indicators on carbon credits.

*Tab.7*

*OLS Regression Results for Impact of Economic Indicators on Carbon Credits*

| **Dependent Variable: DCAR_CRD** | | | | |
|---|---|---|---|---|
| **Method: Least Squares** | | | | |
| **Variable** | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.** |
| | | | | |
| DC_OIL | -136.8995 | 53.28797 | -2.569052 | 0.0206 |
| | | | | |
| DAMS | -24.99608 | 34.89805 | -0.716260 | 0.0442 |
| | | | | |
| DHPI | 39.09383 | 14.17307 | 2.758318 | 0.0140 |
| | | | | |
| DGDP | -1.444987 | 3.213086 | -0.449719 | 0.0389 |
| | | | | |
| DIIP | 2.796746 | 2.199563 | 1.271501 | 0.0217 |

| | | | |
|---|---|---|---|
| R-squared | 0.344019 | Mean dependent var | 110.8680 |
| Adjusted R-squared | 0.180024 | S.D. dependent var | 284.3964 |
| S.E. of regression | 257.5281 | Akaike info criterion | 14.14439 |
| Sum squared resid | 1061131. | Schwarz criterion | 14.39309 |
| Log likelihood | -143.5161 | Hannan-Quinacrine. | 14.19836 |
| Durbin-Watson stat | 2.856512 | | |

*Source: Reserve Bank of India; BSE; Researchers' Calculation*

Table 7 depicts the impact of select economic indicators on carbon credits. Here, the study considered five economic indicators, namely, crude oil, automobile sales, Green exchange index, GDP, and IIP, which act as independent variables. Carbon credits act as the dependent variable. The coefficient value for crude oil on carbon credits is 136.89; the coefficient value for automobile sales on carbon credits is -24.9960; the coefficient value for the green exchange index is 39.093; the coefficient value for GDP is -1.444; the coefficient value for IIP on carbon credits is 2.796. It indicates that crude oil, automobile sales, and GDP are found to hurt carbon credit, suggesting that a one-unit increase in each will decrease carbon credit by -136.89, -24.996, and 1.444, respectively. The green exchange index and IIP are found to affect carbon credit negatively. This indicates that a one-unit rise in the green exchange index and IIP will increase the carbon credit by 39.093 and 2.796, respectively. As the p-values are less than 0.05 for all economic factors, the null hypothesis is rejected, i.e., there is an impact of select economic indicators on carbon credit.

## 5. DISCUSSION

The findings show that different economic and financial factors affect carbon credits differently over time. The VECM analysis shows that, in the long run, the housing price index (HPI) positively affects carbon credits, whereas crude oil and auto sales (AMS) negatively affect them. These findings align with earlier research indicating that asset markets, such as housing markets, can increase credit demand. However, shocks to the energy market often reduce the price of carbon credits (Zhang et al., 2021). (Apergis & Payne, 2018) found little long-term causality between energy consumption and carbon markets. This aligns with the Wald test results, which show no significant long-term causal relationship between carbon credits and the economic factors of crude oil, AMS, and HPI. In the short term, crude oil, AMS, and GDP are negatively associated with a drop in carbon credits, with coefficients of 136.89, 24.996, and 1.444, respectively. Other new economies also reported comparable short-run adverse impacts of oil on GDP and carbon markets (J. Li et al., 2025). Conversely, the Index of Industrial Production (IIP) and the Green Exchange Index have a significant and positive short-run impact, with values of 39.093 and 2.796, respectively. This confirms the results of Lee & Brahmasrene (2019), who indicated that financial development and industrial activity play a crucial role in facilitating carbon trading.

## 6. CONCLUSIONS

The study concluded that there is a mix of positive and negative impacts of various economic factors on carbon credits. The economic factors of crude oil and AMS negatively affect carbon credits, while the economic factor of HPI positively affects them. The Wald test results suggest that there is no long-run relationship between carbon credits and the economic factors of crude oil, AMS, and HPI. However, GDP is reported to have a negative impact in the short run, and IIP has a positive effect on carbon credits. On the other hand, crude oil, automobile sales, and GDP negatively affect carbon credits. An increase in the Green exchange index and IIP will increase the number of carbon credits. The study concludes that economic factors can positively affect carbon credit prices in the near future, and an increase in these factors could drive demand for carbon credits, boosting the carbon credit market.

Moreover, the results have important policy implications. While embracing low-carbon technology and sustainable investment, regulators and policymakers should fortify market-based mechanisms that promote GDP and industrial growth. A capital tool for supporting investor confidence in sustainable markets is the green exchange index. Under these circumstances, financial innovation via the Green Exchange Index can be a strategic tool to boost market confidence.

Furthermore, this research has specific limitations. Additionally, secondary data were used, and unexpected events such as pandemics or geopolitical crises were not explicitly covered. The study relies on secondary data and does not account for external shocks like pandemics or geopolitical crises. This can be restated to clarify.

To increase generalizability, future studies might compare the carbon credit markets in India with those in other nations, include firm-level variables, and expand the dataset. India's carbon credit market is linked to macroeconomic performance, as this study shows, and greater alignment between economic expansion and environmental objectives will allow the nation to establish itself as a front-runner in the global low-carbon economy.

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Both authors contributed equally to all aspects of this research, including conceptualisation, data curation, formal analysis, investigation, methodology, project administration, supervision, validation, visualisation, writing original draft, and writing review and editing.

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Саїт Софія Ахмед, Пуппілліккаду Віджеш. Зелена економіка в дії: дослідження зв'язку між промисловим зростанням, ринковими силами та рухом вуглецевих кредитів у країнах, що розвиваються – на прикладі Індії. *Журнал Прикарпатського університету імені Василя Стефаника*, **12** (4) (2025), 49-65.

У цьому дослідженні проаналізовано вплив ключових показників економічного зростання на ринок вуглецевих кредитів в Індії, з акцентом на те, як окремі макроекономічні змінні формують динаміку вуглецевих кредитів в економіці, що розвивається. На основі вторинних даних за 11 років, отриманих від Резервного банку Індії (RBI) та BSE India, застосовано комплексні економетричні методи, зокрема розширений тест Дікі-Фуллера (ADF) і тест Філліпса-Перрона (PP) на одиничний корінь, модель корекції помилки (VECM) та регресію найменших квадратів (OLS), щоб дослідити коротко- та довгострокові взаємозв'язки між змінними. Аналіз охоплює ціни на сиру нафту, продажі автомобілів (AMS), індекс цін на житло (HPI), ВВП, індекс промислового виробництва (IIP) та індекс «Green Exchange» - показник ефективності сталих фінансів та довіри інвесторів до ринку вуглецевих кредитів. Ці змінні відображають економічну активність, ринкові настрої та енергетичну залежність, що впливають на ціноутворення та попит на вуглецеві кредити.

Емпіричні результати показують, що ціни на сиру нафту та AMS негативно впливають на вуглецеві кредити, тоді як HPI, ВВП та IIP мають позитивний вплив. Тест Вальда свідчить про відсутність довгострокових взаємозв'язків між вуглецевими кредитами та цінами на нафту, AMS чи HPI. Водночас ВВП, IIP та індекс «Green Exchange» істотно стимулюють вуглецеві кредити в короткостроковій перспективі. Перевірка надійності з використанням даних за 2024 рік підтверджує стабільність виявлених взаємозв'язків у часі.

Дослідження робить висновок, що макроекономічні та промислові показники є визначальними у формуванні коливань вуглецевих кредитів. Посилення промислової продуктивності, розвиток сталих фінансів і узгодження макроекономічної політики з екологічними цілями можуть підвищити ефективність ринку вуглецевих кредитів. Отримані результати є корисними для політиків, інвесторів та екологічних економістів, які прагнуть гармонізувати економічне зростання з цілями скорочення викидів. Досвід Індії також може слугувати стратегічним орієнтиром для інших країн, що розвиваються, які впроваджують сталу систему торгівлі вуглецевими квотами.

**Ключові слова:** вуглецеві кредити, економічне зростання, ВВП, IIP, VECM, кліматична політика, Індія.