

Unveiling a Dynamic Relation Between Transport Emissions and Ecological Footprint in Growth-oriented Asian Economies

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Rakesh Shahani¹  and Kartikay Ahluwalia¹

Abstract

Purpose: The study makes an attempt to investigate the long-term dynamic relation between CO₂ emissions from liquid fuel consumption by the transport sector (TR) and the ecological footprint (EFP) of two Asian emerging giants, namely, China and India. Four other variables, ‘Urbanisation’, ‘Trade Openness’, ‘ICT’ and ‘GDP’ have also been included under the study as control variables. The period of study is 30 years (1987–2016), and the data have been sourced from World Development Indicators and Global Footprints Network.

Methodology: The methodology includes testing for co-integration amongst variables by applying the ARDL co-integration model (with a single breakpoint) and its non-linear counterpart, NARDL. The error correction, testing for asymmetric impact and long-run elasticity are other aspects considered under the study.

Findings: Co-integration was established at 1% level for both countries, both under the ARDL and NARDL models. The long-run impact of TR on EFP was positive for both countries, with elasticity between TR and EFP being highly inelastic for India and somewhat elastic for China. The asymmetric impact of TR on EFP was not seen in either of the two countries in the long run. The long-run adjustment process through the ECM(–1) term was found to be stable, but the speed of adjustment was moderate @7% p.a. for China and slow @0.3% p.a. for India. All three model diagnostics were found to be highly satisfactory.

¹Department of Business Economics, Dr. Bhim Rao Ambedkar College, University of Delhi, India

Corresponding author:

Rakesh Shahani, Department of Business Economics, Dr. Bhim Rao Ambedkar College, University of Delhi 110094, India.

E-mails: rakesh.shahani@bramb.du.ac.in; rakesh.shahani@gmail.com



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Study Implications: Adjustment speed at 7% p.a. for China and 0.3% p.a. indicates that for India, the long-run relation between TR and EFP would only be reached after a few years, which gives sufficient time for the policy makers to act towards deciding on the roadmap to sustainable development. Then, for India, the elasticity between TR and EFP was inelastic in the long run; this was fairly elastic for China, which implied that China was strategically better placed and well prepared for the transformation to renewable energy to run the TR, while India may have to continue with the traditional fuels for some more time.

Keywords

ARDL, asymmetry, co-integration, ecological footprint, NARDL

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Introduction

Fossil fuels, central to manufacturing, are a major driver of economic growth in both resource-rich and resource-scarce economies. Transport, which serves as a catalyst in economic growth, has experienced significant expansion over recent decades, making this sector a leader in energy consumption, accounting for about 25% of global GHG emissions in 2021 (UN Fact Sheet, 2021). This surge, fuelled by globalisation, urbanisation, and trade, has intensified fossil fuel use and environmental degradation. With only 3.7% of its energy from renewables and 96.3% from fossil fuels, immediate regulatory actions and investment in sustainable infrastructure are highly critical, and hence the sector requires the highest priority (IRENA, 2021).

Global efforts to cut fossil fuel use in transport have shown promise but remain concentrated in developed nations. For example, a US study (1977–2007) by Brown-Steiner et al. (2016) found black carbon emissions from diesel trucks and trains dropped despite rising freight volumes, thanks to policies like transport clustering and regulatory enforcement. Nonetheless, such progress is limited in developing countries.

Despite evident environmental harm, many nations hesitate to act due to the substantial investment required for cleaner fuels and economic significance of the transport sector (TR) in enhancing productivity, employment, property values and other benefits (Pradhan et al., 2024). Scholars suggest non-conflicting policies, which demand understanding the interplay among growth, energy, and CO₂ emissions.

Beyond GHGs, transport also causes noise pollution and waste generation. According to OECD (2021), transport's energy share is highest in the US (37.5%), UK (33%), and Switzerland (31%), compared to 15% in India and China, which actually contradicts developed economies taking proactive measures to combat transport emissions. Within transport, road transport accounts for about 75% of CO₂ emissions, the rest being shared by air and rail (Saboori et al., 2014). In emerging economies, industrial energy use remains high—China (49%),

Indonesia (37%), India (38%), while in developed nations it has fallen significantly—US (17%), UK (18%) (IRENA, 2021). This points to a relocation of energy-intensive industries from developed to developing countries.

Shifting the focus to the present study, leaving aside overall emissions, research reveals that sector-specific energy consumption remains largely unexplored. Although for emissions, most studies have considered CO₂ or SO₂ emissions as their proxy for environmental degradation, the sector-wise breakup of these emissions has been largely ignored, which becomes one of the motivations of the present study.

The study investigates the long-run relationship between transport emissions and environmental degradation in two emerging Asian economies, China and India, the criterion for sample choice being their rapid economic growth amongst developing nations. The study employs ecological footprint (EFP) and liquid fuel consumption by transport as main proxies besides four control variables: Urbanisation, trade openness, ICT, and GDP. Including control variables prevents omission bias and aligns the study with previous studies (Frey et al., 2006; Hassan et al., 2019). A 30-year dataset, log-transformed, is used for analysis. EFP data from the Global Footprint Network (2023) covers six land categories and reflects the environmental cost of production and waste, adjusted for Earth's regenerative capacity (Nathaniel & Khan, 2020; Rashid et al., 2018).

Strand et al. (2021) report that rising global EFP is driven by poor natural resource management and weak environmental regulation. Innovation in technology is cited as a key solution to reversing ecological degradation. Santos (2017) links regulatory failure to the absence of a global enforcement body.

Before discussing methodology, the study reviews relevant literature, categorised into two groups: Studies analysing transport emissions and studies examining related control variables. The impact of some of the control variables on the environment has been found to be country-specific, for example, most studies find that urbanisation's environmental effects are country-specific—harmful in China and Qatar (Charfeddine, 2017; Sheng & Guo, 2016), but beneficial in the UAE and MENA countries (Charfeddine & Ben Khediri, 2016; Charfeddine & Mrabet, 2017). On the other hand, ICT, often measured by mobile usage or subscriptions, is generally linked to lower environmental degradation. For instance, Salahuddin et al. (2016) found mobile use was negatively related to CO₂ in OECD countries, while Asongu et al. (2017) found similar results in Sub-Saharan Africa. Hussain et al. (2023) showed that ICT combined with urbanisation and electricity use reduced EFP. Contrastingly, in Iran, ICT increased industrial CO₂ emissions (Shabani & Shahnazi, 2019). Then, the existence of an asymmetric impact of ICT on emissions was reported in a study on Tunisia (Amri et al., 2019).

Studies focusing on the main variable, transport emissions, include Brown-Steiner et al. (2016), who showed reduced emissions through policy and enforcement. Others, including Ayadi and Hammami (2015) and Sasana and Aminata (2019), stress that without strong regulation, environmental damage is unavoidable. Abbes and Bulteau (2018) found that transport accounted for 92% of Tunisia's GHG emissions.

Transport energy consumption was found to be closely linked to CO₂ emissions in many studies. A study by Nasreen et al. (2020) found bidirectional relationships

between CO₂ and transport energy in 18 countries. Saboori et al. (2014) showed long-run, positive links among CO₂, economic growth, and road sector energy use across OECD countries. The study showed that impulses of road sector energy consumption towards CO₂ emissions lasted longer than impulses towards economic growth, implying long-run policies could be framed for shifting to renewable fuels and could benefit in mitigating GHG emissions.

With respect to the relation between transport and EFP, there have been only a handful of studies, like Hussain et al. (2023), which showed that a reduction in EFP was possible by increasing expenditure on transport infrastructure and through sustained economic growth. Then, Satrovic et al. (2024) concluded that transport energy and natural resource depletion were responsible for the rise in EFP, while technological innovation was seen as reducing the same.

Then, apart from emissions, another TR variant becoming popular amongst researchers is transport infrastructure and the same was considered in studies including Churchill et al. (2021), Pradhan et al. (2024), Acheampong et al. (2022), amongst others. The variable transport infrastructure with both positive and negative multiplier effects, positive in terms of saving travel time and costs, increasing employment (Pradhan et al., 2024), while negative being the use of environment-unfriendly products; cement, concrete and heavy-duty equipment by infrastructure projects themselves. Churchill et al. (2021) found that a 1% rise in transport infrastructure was associated with a 0.4% rise in CO₂ emissions.

Research Gap

The literature review revealed limited studies examining the role of control variables while modelling the transport-environment relation, particularly in emerging markets. This study fills the gap by including such control variables to bring out the deterministic role played by each and every control factor towards the environment, even though the study objective was to establish the relation between transport emissions and EFP. Furthermore, the review apprised us that the research area, transport emissions and EFP linkages was highly under-researched as the study could figure out only a few studies alongside developed economies. The study, which includes India and China, two developing economies, would try to compare the outcome of the current research with the outcome in developed economies.

A unique feature of this study was its dual modelling approach using both quasi-linear ARDL (with structural break) and non-linear NARDL models. This methodology choice stems from the BDS test results, which indicated non-linear behaviour in EFP. While ARDL models (Pesaran et al., 2001) would handle mixed-order integration, assuming linearity by incorporating structural breaks, NARDL tends to focus on nonlinearities (Shin et al., 2014), allowing better modelling of complex dynamics. To the best of our knowledge, no study has applied both ARDL variants to explore this relationship.

The rest of the article is structured as follows: The second section presents descriptive statistics, the third section explains the methodology employed, the

fourth section provides empirical results, and finally, the fifth section presents a conclusion, study limitations and policy implications, followed by references in the sixth section.

Summary Information and Descriptive Statistics of the Variables

Table 1 summarises the six variables along with their units of measurement and data sources, and is shown under three columns, sources of data being the World Bank (2023) and Global Footprints Network (2023). Table 2 compares descriptive statistics of these variables for India and China over the 30-year period (1987–2016). China's average EFP was four times India's, with CO₂ emissions from transport in China being about 2.2 times higher. For the four control variables, China also consistently reported higher averages.

Standard deviation, which indicates variability, was higher for China for five out of six variables. India showed more variability only in TR emissions, suggesting inconsistent trends compared to China's more stable emission control. Skewness results showed a strong positive skew for China's EFP, implying more years with values above the average. India's EFP also had a positive skew, but less pronounced, suggesting a more balanced distribution. India's TR skewness was much higher than China's, indicating frequent years of emissions above the average. Kurtosis values were negative for most variables, indicating flatter, more normal-like distributions, suggesting no large distribution asymmetries for either country.

In summary, Table 2 gives preliminary insight into the trends of two emerging economies. For India, TR emissions seem to be a major driver of EFP changes, while in China, other sectors such as industry and power may be more responsible.

Table 1. Summary Information About the Variables Included in the Study.

Sr No	Name of the Variable	Unit of Measurement	Source of Data
1.	Urbanisation (URB)	Urban pop (% of total pop)	World Development Indicators
2	Economic growth (GDP)	GDP per capita constant 2015 prices	World Development Indicators
3	Ecological footprint (EFP)	Global hectares per capita	Global Footprints Network GFN (2023)
4.	Trade openness (TO)	Merchandise {sum of exports and imports (% of GDP)}	World Development Indicators
5.	Mobile usage (MU)	Mobile cellular subscription (per 100 persons)	World Development Indicators
6.	CO ₂ emissions from liquid fuel cons by transport (TR)	Liquid fuel consumption (kt)	World Development Indicators

Table 2. Statistical Description of Variables for the Period 1987–2016.

Parameter	EFP		Urbanisation		Trade Openness		ICT-mobile Subscriptions		GDP (Crores)		Emissions from Transport	
	India	China	India	China	India	China	India	China	India	China	India	China
Mean (μ)	0.50	2.17	8.51	38.99	24.340	42.306	20.79	29.64	102.8	442.3	3.11	7.43
Std. Dev. (σ)	0.143	0.759	2.508	10.206	10.379	9.994	30.21	34.806	5.52448E+11	3.39443E+12	1.34	1.1
Skewness (S)	0.118	0.474	0.307	0.212	0.519	0.825	1.042	0.805	0.722	0.804	0.750	0.373
Kurtosis (K)	-1.95	-1.35	-1.09	-1.256	-0.949	-0.256	-0.55	-0.799	-0.508	-0.544	0.201	-1.157

This aligns with findings by Shang et al. (2024), who observed that China's emissions reduction came from a gradual switch to low-carbon fuels, thereby taking the burden off the TR.

Methodology

The methodology revolves around two co-integration variants: ARDL with a single structural break and NARDL, choice being based upon results obtained under the BDS test statistics. Hence, before any discussion on the two variants, the study explores the methodology employed for the BDS test statistics.

BDS Test

BDS test statistic (Brock et al., 1987) determines whether data is independently and identically distributed (I.I.D), and the study has applied BDS on raw data with 'm' embedded dimension with histories being rolled over in the following manner:

$$y_1^m = y_1, y_2, y_3, \dots, y_m, y_2^m = y_2, y_3, y_4, \dots, y_{m+1}, y_3^m = y_3, y_4, y_5, \dots, y_{m+2} \text{ and so on.}$$

Null Hypothesis

H_0 : I.I.D. time series data.

H_A : Time series data is not I.I.D.; hence, non-linear

Based upon the BDS results obtained (shown under Table 3), we decided to develop two models: ARDL with a single structural break and NARDL. Further, with non-linearity being proved, the study introduced a Dummy variable for the dependent variable in the ARDL model, thus making this model a quasi-linear model.

Model Representation (ARDL with Single Structural Break)

The section discusses the ARDL co-integration Model with a single structural break for the variable EFP; model representation for the same is given as Equation 1.

$$\begin{aligned} \Delta \ln.EFP_{i,t} &= \beta_{1,i} + \beta_{1,i,BD_i}^{\#} D_{i,t} + \beta_{2,i} \ln.EFP_{i,t-1} + \beta_{3,i} \\ &\ln.TR_{i,t-1} + \beta_{4,i} \ln.GDP_{i,t-1} + \beta_{5,i} \ln.TO_{i,t-1} + \beta_{6,i} \ln.URB_{i,t-1} + \beta_{7,i} \\ &\ln.MU_{i,t-1} + \sum_{m=1}^{n_1} (\beta_{8,i} \Delta \ln.EFP_{i,t-m}) + \sum_{m=0}^{n_1} (\beta_{9,i} \Delta \ln.TR_{i,t-m}) + \\ &\sum_{m=0}^{n_1} (\beta_{10,i} \Delta \ln.GDP_{i,t-m}) + \sum_{m=0}^{n_1} (\beta_{11,i} \Delta \ln.TO_{i,t-m}) + \\ &\sum_{m=0}^{n_1} (\beta_{12,i} \Delta \ln.URB_{i,t-m}) + \sum_{m=0}^{n_1} (\beta_{13,i} \Delta \ln.MU_{i,t-m}) + e_{i,t} \end{aligned} \quad (1)$$

For Equation 1, $\Delta \ln.EFP_{i,t}$ is the logarithmic change in EFP, model dependent variable, with 't' being the time period and 'i' representing two countries; $i = 1, 2, 1$

(India) or 2 (China). Equation 1 has ' β_1 ' as intercept while ' $\beta_{1,t}^{\#}$ ' slope coefficient of Intercept Dummy (D_i) reflecting structural break of dependent variable, EFP. As stated above, the inclusion of a structural break is based upon the BDS test results and applies Perron's Innovative Outlier Method (Perron, 1994), following asymptotic one-sided ' p ' values. Dummy Variable ($D_{i,t}$) takes the value as:

$$\begin{cases} 1 & \text{if } t \geq BD_i \\ 0 & \text{if } t < BD_i \end{cases} \cdot BD : \text{Break Date for } i^{th} \text{ country}$$

' β_2 ' is the slope coefficient of the first lag of dependent variable EFP, while next five terms, ' β_3 ' to ' β_7 ' are slope coefficients of first lag of five independent variables, namely, TR, GDP, URB, TO and MU, respectively. Five further independent variables at their first lags together with the dependent variable EFP make up the long-term relation under ARDL.

The term $\sum_{m=1}^{n_1} (\beta_{8,i} \Delta \ln.EFP_{i,t-m})$ depicts log change in dependent variable EFP and has been included as a regressor, with ' r_1 ' being AIC determined lags.

Similarly, the term for transport is $\sum_{m=0}^{n_1} (\beta_{9,i} \Delta \ln.TR_{i,t-m})$, ' n_1 ' being the lags (AIC), and the same goes for other independent variables. Further, with a limited number of observations under study, a restriction of Max '2' lags for both dependent and independent variables was considered, that is, $m = \text{Max of Lags}$ (0,1,2) for independent and $m = \text{Max of Lags}$ (1,2) for dependent variable. These terms are then summed up and collectively make up the short-run relation. Finally, $e_{i,t}$ is the stochastic error term of Equation 1.

Model Representation (NARDL)

NARDL model (Shin et al., 2014) is an asymmetric expansion of ARDL and decomposes our independent variable, TR, into positive and negative values, keeping rest of the variables unchanged as given under Equation 1. NARDL model for dependent variable EFP is given as Equation 2 below:

$$\begin{aligned} \Delta \ln.EFP_{i,t} &= \lambda_{1,i} + \lambda_{1,i,BD_i}^{\#} D_{i,t} + \lambda_{2,i} \ln.EFP_{i,t-1} + \lambda_{3,i}^+ \ln.TR_{i,t-1}^+ + \lambda_{3,i}^- \ln.TR_{i,t-1}^- + \lambda_{4,i} \\ \ln.GDP_{i,t-1} &+ \lambda_{5,i} \ln.TO_{i,t-1} + \lambda_{6,i} \ln.URB_{i,t-1} + \lambda_{7,i} \ln.MU_{i,t-1} + \sum_{m=1}^{n_1} (\lambda_{8,i} \Delta \ln.EFP_{i,t-m}) + \\ &\sum_{m=0}^{n_1(A)} (\lambda_{9,i}^+ \Delta \ln.TR_{i,t-m}^+) + \sum_{m=0}^{n_1(B)} (\lambda_{9,i}^- \Delta \ln.TR_{i,t-m}^-) + \sum_{m=0}^{n_1} (\lambda_{10,i} \Delta \ln.GDP_{i,t-m}) + \\ &\sum_{m=0}^{n_1} (\lambda_{11,i} \Delta \ln.TO_{i,t-m}) + \sum_{m=0}^{n_1} (\lambda_{12,i} \Delta \ln.URB_{i,t-m}) + \sum_{m=0}^{n_1} (\lambda_{13,i} \Delta \ln.MU_{i,t-m}) + u_{i,t} \end{aligned} \quad (2)$$

where

$$\lambda_3^+ = \begin{cases} \lambda_3 & \text{if } \lambda_3 > 0 \\ 0 & \text{if } \lambda_3 \leq 0 \end{cases} \text{ and } \lambda_3^- = \begin{cases} \lambda_3 & \text{if } \lambda_3 < 0 \\ 0 & \text{if } \lambda_3 \geq 0 \end{cases}$$

$$\lambda_9^+ = \begin{cases} \lambda_5 & \text{if } \lambda_5 > 0 \\ 0 & \text{if } \lambda_5 \leq 0 \end{cases} \text{ and } \lambda_9^- = \begin{cases} \lambda_5 & \text{if } \lambda_5 < 0 \\ 0 & \text{if } \lambda_5 \geq 0 \end{cases}$$

As already stated, the variable TR in Equation 2 is decomposed as TR⁺ and TR⁻, TR⁺ takes a positive value when variable TR is positive, while for all zero and negative values of variable TR, TR⁺ takes a value as '0'. Again, variable TR⁻ takes a negative value if TR is negative, while for all other values of TR, TR⁻ takes a value as '0'.

Test for Long-term Co-integration: Partial 'F' Bounds Test

The existence of co-integration under both models is tested by applying partial 'F' bounds test (Pesaran et al., 2001). We set up two null hypotheses, one for ARDL and the second for NARDL, under 'F' bounds test

$$HO_1: \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0 \text{ (for ARDL Equation 1)}$$

$$HO_2: \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = 0 \text{ (for NARDL Equation 2)}$$

Null gets rejected if 'F' computed > Upper Bound critical (Table 5)

Long-term Relation: Elasticity and Asymmetry

The section discusses the long-run relation amongst the variables, which is established only when co-integration is proved. Since results from the partial 'F' bounds test confirm the establishment of co-integration both for ARDL and NARDL models and for both countries, India and China, we go ahead and establish Equation 3, the long-term relation.

$$\begin{aligned} \ln.EFP_{i,t} = & \delta_{1,i} + \delta_{1,i,BD_1} \#D_{i,t} + \sum_{m=1}^{g_1} (\delta_{2,i} \ln.EFP_{t-m}) + \sum_{i=0}^{g_2} (\delta_{3i} \ln.TR_{t-i}) + \\ & \sum_{i=0}^{g_2} (\delta_{3i} \ln.GDP_{t-i}) + \sum_{i=0}^{g_2} (\delta_{3i} \ln.TO_{t-i}) + \sum_{i=0}^{g_2} (\delta_{3i} \ln.UR_{t-i}) + \\ & \sum_{i=0}^{g_2} (\delta_{3i} \ln.MU_{t-i}) + v_{i,t} \end{aligned} \quad (3)$$

Notation g_1 , in Equation 3, represents lags of dependent variable EFP and g_2 lags for all five independent variables, all following the AIC criteria. Further, long-run elasticity of EFP with respect to TR is established by developing Equations 4 and 5. Considering 'L', as the backshift operator, we develop Equation 4.

$$A(L, g_1) \ln.EFP_{1,t} = \delta_1 + \delta_{1,i,BD_1} \#D_{i,t} + B(L, g_2) \ln.TR_t + e_{1,t} \quad (4)$$

To obtain long-run elasticity, we make use of Equations 3 and 4 and develop Equation 5 as follows

$$\frac{A(L, g_1)}{B(L, g_2)} = \frac{1 - \delta_{2,1} - \delta_{2,2} - \dots - \delta_{2,g_1}}{\delta_{3,0} + \delta_{3,1} + \delta_{3,2} + \delta_{3,3} \dots \delta_{3,g_2}} \quad (5)$$

Next, consider Equation 2 again, applying ‘Wald’ to test the asymmetric impact of TR on EFP with null (H_0): $\pi^+ = \pi^-$, where $\pi^+ = \frac{\lambda_3^+}{\lambda_2}$ and $\pi^- = \frac{\lambda_3^-}{\lambda_2}$ (from Equation 2).

Short-term Relation: Asymmetry and Error Correction Towards Equilibrium

The section discusses short-run relations among the variables and tries to build an Error Correction Model, which corrects for short-run disequilibrium and traces the path towards long-run equilibrium (Equations 6 and 7 below)

$$\begin{aligned} \Delta \ln.EFP_{i,t} = & \partial_{1,i} + \partial_{1,i,BD_1} \#D_{i,t} + \partial_2 EC_{i,t-1} + \sum_{m=1}^{r_2} (\partial_{3,i} \Delta \ln.EFP_{t-m}) + \\ & \sum_{m=0}^{n_2} (\partial_{4,i} \Delta \ln.TR_{t-m}) + \sum_{m=0}^{n_2} (\partial_{5,i} \Delta \ln.GDP_{t-m}) + \sum_{m=0}^{n_2} (\partial_{6,i} \Delta \ln.TO_{t-m}) + \\ & \sum_{m=0}^{n_2} (\partial_{7,i} \Delta \ln.URB_{t-m}) + \sum_{m=0}^{n_2} (\partial_{8,i} \Delta \ln.MU_{t-m}) + e_{2,t} \end{aligned} \quad (6)$$

Equation 6 provides the short-run equation under ARDL (with a single structural break) with r_2 being lags of EFP and n_2 as lags of independent variables TR, GDP, TO, URB and MU, both follow AIC criteria. The term $EC_{i,t-1}$ with coefficient ∂_2 represents the error correcting term, while $\partial_{4,0}$ is the short-run price transmission elasticity coefficient from variable TR to EFP.

Equation 7 provides an error correction and adjustment mechanism under NARDL with the TR variable decomposition as TR^+ and TR^- under a short-run framework.

$$\begin{aligned} \Delta \ln.EFP_t = & \gamma_{1,i} + \gamma_{1,i,BD_1} \#D_{i,t} + \gamma_2 EC_{i,t-1} + \sum_{m=1}^{r_2} (\gamma_{3,i} \Delta \ln.EFP_{t-m}) + \\ & \sum_{m=0}^{n_{2,A}} (\gamma_{4,i}^+ \Delta \ln.TR_{t-m}) + \sum_{m=0}^{n_2} (\gamma_{4,i}^- \Delta \ln.TR_{t-m}) + \sum_{m=0}^{n_2} (\partial_{5,i} \Delta \ln.GDP_{t-m}) \\ & + \sum_{m=0}^{n_2} (\partial_{6,i} \Delta \ln.TO_{t-m}) + \sum_{m=0}^{n_2} (\partial_{7,i} \Delta \ln.URB_{t-m}) + \sum_{m=0}^{n_2} (\partial_{8,i} \Delta \ln.MU_{t-m}) + e_{3,t} \end{aligned} \quad (7)$$

Further, for both equations, Equation 6 and 7, the term EC_{t-1} shows how fast the market would adjust to achieve long-run equilibrium, implying that a shock under the system has an adjustment mechanism as ∂_2 (ARDL) and γ_2 (NARDL). The ‘ n ’ period shock adjustment being $1-(1-\partial_2)^n$ and $1-(1-\gamma_2)^n$ for two models, respectively.

NARDL also provides useful information on short-run asymmetry, with null defined as $\sum_{m=0}^{n_{2,A}} (\gamma_{4,i}^+) = \sum_{m=0}^{n_{2,B}} (\gamma_{4,i}^-)$ (from Equation 7).

Results

This section summarises findings from Tables 3 to 9. Tables 3 and 4 present BDS test results, indicating non-linearity in the EFP variable for both India and China.

Table 3. BDS Results for Our Variable EFP (China).

Dimension	BDS Statistic	p	Result
2	0.186464	.0000	Null rejected, non-linearity is detected at all dimensions
3	0.300130	.0000	
4	0.369431	.0000	
5	0.406886	.0000	
6	0.420525	.0000	

Table 4. BDS Results for Our Variable EFP (India).

Dimension	BDS Statistic	p	Result
2	0.072266	.0000	Null rejected, non-linearity is detected at all dimensions
3	0.177897	.0000	
4	0.276653	.0000	
5	0.321174	.0000	
6	0.365332	.0000	

Table 5. Partial 'F' Bounds Test ARDL (with Dummy) Model.

Model Specification	Country	Dummy Date & 'p' Value in Parenthesis	'F' Bounds (Computed Value)	Critical Table Value at 5%* and 1%**		Inference
				Lower Bound I(0)	Upper Bound I(1)	
EFP as f (TR, URB, TO, ICT and GDP)	India	1995 (.0084)	5.163	2.39* 3.06**	3.38* 4.15**	Co-integration is established at 1% level
	China	2002 (.0993)	8.229	2.39* 3.06**	3.38* 4.15**	Co-integration is established at 1% level

Notes: $H_0: \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$ (see Equation 1)

Table Result: Co-integration is established for both India and China.

Dummy Coefficients included in ARDL were significant for India at 1% and for China at 10% justifying inclusion of structural break for India and partially justifying for China. The significance levels are 5%(*) and 1%(**).

The rejection of the null hypothesis across all embedding dimensions supports the use of non-linear models; ARDL (with structural break) and NARDL.

Following this, Tables 5 and 6 display results from the Partial F-Bounds test for long-run co-integration. For both India and China, and under both ARDL and NARDL models, the computed F-statistics exceeded upper bound at 1% level, confirming long-run co-integration.

The co-integration established for India and China enabled long-run analysis. Table 7 shows that TR significantly and positively affects EFP in both countries, at 1% level for India and 10% for China. For India, ICT negatively impacts EFP, while in China, GDP, TO, and URB positively affect EFP, and ICT has a negative

Table 6. Partial 'F' Bounds Test NARDL Model.

Model Specification	Country	'F' Bounds (Computed Value)	Critical Table Value at 5%* and 1%**		Inference
			Lower Bound I(0)	Upper Bound I(1)	
EFP as f (TR, URB, TO, ICT and GDP)	India	7.72	2.27* 2.88**	3.28* 3.99**	Co-integration is established at 1% level
	China	11.41	2.27* 2.88**	3.28* 3.99**	Co-integration is established at 1% level

Notes: $H_0: \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = 0$ (see Equation 2)

Table result: Co-integration is established for both India and China. The significance levels are 5%(*) and 1 %(**).

Table 7. Long-run Results Under Both ARDL and NARDL Model.

Regressors (Long-run)	(EFP China)		(EFP India)	
	Coefficient	p Value	Coefficient	p Value
EFP(-1)	0.51	.0002	0.7207	.0058
TR(-1)	0.202	.0876	0.6208	.0208
GDP(-1)	3.304	.0001	-0.3492	.3008
TO(-1)	0.578	.000	-0.0655	.2426
ICT(-1)	-0.059	.0004	-0.0577	.0063
URB(-1)	-7.83	.0003	-12.73	.3697
Dummy for regressand	-0.0872	.0993	0.3083	.0093
TR⁺(-1) (λ_3^+)	-0.232796	.0674	-0.1395	.1960
TR⁻(-1) (λ_3^-)	-3.9157	.0022	0.2664	.1950
Coeff. of EFP(-1) from NARDL (λ_2) for testing asymmetry	0.614064	-	-0.7276	-
Asymmetric impact of TR on EFP $\pi^+ = \pi^- = 0$ (Null: No asymmetry: F Wald) where $\pi^+ = \left(\frac{\lambda_3^+}{\lambda_2^+}\right)$ and $\pi^- = \left(\frac{\lambda_3^-}{\lambda_2^-}\right)$; λ_3^+, λ_3^- and λ_2 are coeff. from Equation 2	<u>China</u> F computed: 0.143, 'p' statistics: .709, no long-run asymmetry. <u>India</u> F computed: 2.787, 'p' statistics: .1336, no long-run asymmetry.			
Long-run elasticity of EFP with respect to TR	Highly inelastic for India at 0.449, fairly elastic at 2.43 for China			

Notes: 1. Model selection method: AIC.

2. Model selected: China: ARDL (2, 0, 2, 1, 1, 2); India ARDL (1, 1, 2, 0, 2, 2); China NARDL (1, 0, 1, 0, 2, 2, 0); India NARDL (2, 2, 2, 2, 1, 2, 1).

3. For long-run elasticity of EFP with respect to TR, the applicable formula from Equation 5 is given as: $\frac{A(L, g_1)}{B(L, g_2)}$.

influence. These findings align with Hussain et al. (2023) and Salahuddin et al. (2016).

The Wald F-test under NARDL confirmed no long-run asymmetry of TR on EFP in either country. Long-run elasticity of TR on EFP was highly inelastic for India (0.449) and fairly elastic for China (2.43), suggesting China's gradual transition toward alternative fuels, while India remains reliant on fossil fuels.

In the short run (Table 8), TR, TO, and ICT impact EFP in India; TR and TO positively, ICT negatively. In China, all variables influence EFP, with ICT again showing a negative effect, and the rest of the variables positively. Short-run elasticity of TR on EFP remained inelastic in both nations, showing limited flexibility. No evidence of short-run asymmetry was seen under the study. The ECM(-1) term confirmed stable but slow adjustment: Faster in China than in India.

Table 9 presents diagnostics: Breakpoint ADF tests showed mixed stationarity across variables, justifying ARDL modelling. Results from BG-LM and BPG tests indicated no serial correlation or heteroscedasticity. These diagnostics support the reliability of the results.

Conclusion and Implications

This study empirically examined the long-term dynamic relationship between CO₂ emissions from liquid fuel consumption in the TR and EFP in China and India, using ARDL and NARDL models. Co-integration was confirmed at a 1%

Table 8. Short-run Results and Error Correction.

Regressors (Short run)	(EFP China)		(EFP India)	
	Coefficient	p Value	Coefficient	p Value
D(EFP(-1))	0.297	.007	0.35	.002
D(TR)	0.009	.023	0.596	.0005
D(TR(-1))	–	–	0.3	.000
D(GDP)	–	–	–	–
D(GDP(-1))	0.84	.001	–	–
D(ICT)	-0.08	.009	-0.004	.0126
D(ICT(-1))	–	–	-0.006	.0391
D(URB)	0.065	.04	–	–
D(URB(-1))	–	–	–	–
D(TO)	0.35	.00	0.09	.003
D(TO(-1))	–	–	0.08	.009
ECM(-1)	-0.07	.00	-0.0032	.00
Price transmission (elasticity)	Highly inelastic		Fairly inelastic	
Asymmetry (short-run)	Does not exist		Does not exist	

Notes: 1. Short-run elasticity of EFP w.r.t TR: We consider contemporaneous slope coefficients of the change variable TR.

2. Asymmetry is tested by equating the two terms: $\sum_{m=0}^{n_{2,A}} (\gamma_{4i}^+) = \sum_{m=0}^{n_{2,B}} (\gamma_{4i}^-)$.

3. For error correction we consider lagged ECM term coefficient which must be negative and significant.

Table 9. Diagnostics.

Variable	India		China	
	Level	1st Diff	Level	1st Diff
EFP	-67.42803 ($<.01$)	–	-2.877 (.749)	-5.178 (.044)
URB	1.991784 (.9997)	-0.527839 (.08712)	-2.211453 (.2070)	-0.697107 (.08311)
GDP	1.244946 (.9977)	-4.690447 (.0008)	-0.410913 (.8942)	-2.46640 (.0340)
TO	-1.910244 (.3232)	-5.392260 (.0001)	-1.696647 (.4220)	-3.578047 (.0130)
ICT	-0.668531 (.8394)	-3.827251 (.0074)	-6.773738 (.0000)	–
TR	-0.021051 (.9485)	-4.011752 (.0048)	-0.562592 (.8642)	-6.354847 (.0000)
	ARDL model (India)		ARDL model (China)	
A. BPG heteroscedasticity test[#]				
Obs. R^2	8.473628		2.268307	
Probability χ^2	.6704		.3217	
B. BG-LM serial corr. test*				
Obs. R^2	4.467508		7.019348	
Probability χ^2	.1071		.8563	

Notes: 1. Break date; EFP China was in 2002, and EFP India was in 1995.

2. $\Delta EFP_t = \beta_1 + \beta_1^* D_{EFP,t} + (\beta_2 - 1)EFP_{t-1} + \sum_{i=1}^m \beta_{3i} \Delta EFP_{t-i} + u_t$ is the Breakpoint ADF test equation for variable EFP with single break point, ΔEFP_t is change in EFP in period t , β_1 represents intercept, $\beta_1^* D_{EFP,t}$ being single break intercept, and Dummy taking value of '1' for observations falling after break date of EFP and '0' before. The break is validated if β_1^* is statistically significant. Term EFP_{t-1} tests for stationarity with $(\beta_2 - 1)$ as coefficient, where 't' computed is compared with ADF 't' tau tables. Next term $\sum_{i=1}^m \beta_{3i} \Delta EFP_{t-i}$ removes serial correlation, and u_t is the random error term. Using a similar methodology, we construct the stationary equation for our other remaining variables.

[#]BPG Heteroscedasticity test first determines R^2 of auxiliary equation $u_t^2 = \gamma_1 + \gamma_2 X_{2t} + \gamma_3 X_{3t} + \dots + \gamma_k X_{kt}$, followed by $n.R^2_{aux} \sim \chi^2_{m-1}$; Null: No heteroscedasticity, that is, $\gamma_2 = \gamma_3 = \gamma_4, \dots, = \gamma_k = 0$.

^{*}BG-LM serial correlation: The test also constructs an auxiliary equation: $u_{EFP} = \beta_1 + \beta_2 EFP_{t-1} + \beta_3 EFP_{t-2} + \dots + \beta_p EFP_{t-p} + \rho_1 u_{EFP,t-1} + \rho_2 u_{EFP,t-2} + \dots + \rho_m u_{EFP,t-m} + e_t$, number of lags of regression and error term being 'p' and 'm', respectively, 'p' > 'm'. Null: $\rho_1 = \rho_2 = \dots, \rho_m = 0$ (no serial correlation between residuals). Reject the null when $R^2(n-p) > \chi^2_m$. Figures in parentheses are 'p' values.

significance level for both countries. In the long run, TR had a positive impact on EFP; highly inelastic for India and somewhat elastic for China. No asymmetric impact of TR on EFP was detected.

In the short run, TR also influenced EFP with inelastic elasticity in both countries. The ECM(-1) coefficient was negative and stable, indicating adjustment toward equilibrium; moderate (7% p.a.) for China and very slow (0.3% p.a.) for India.

Three key observations emerge: (a) the absence of asymmetry may stem from limited negative growth years in TR and the composite nature of EFP; (b) elasticity contrasts: India's inelastic versus China's elastic long-run TR-EFP link; and (c) different speeds of long-run adjustment.

These findings do provide valuable policy insights. India's slower pace suggests time for planning sustainable transport policies. China's relatively elastic long-run response and faster adjustment indicate better readiness for energy transition. For both nations, inelastic short-run elasticity highlights challenges like poor substitutability and infrastructure gaps. Thus, long-term planning is essential, especially for India, where short- and long-run patterns show little divergence.

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ORCID iD

Rakesh Shahani  <https://orcid.org/0000-0003-4916-2740>

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