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Trade Embedded Emissions in the Indian Fruit Exports: An Econometric Analysis

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ABSTRACT

India's expanding role in global trade, particularly in agriculture, has contributed significantly to economic growth; however, it has also raised concerns regarding trade-embedded carbon emissions. This study examines the environmental implications of India's fruit exports over 32 years (1990–2022), with a focus on emissions embedded in trade flows to major destinations, including Bangladesh, the UAE, the UK, and others. Employing panel data econometrics within a gravity model framework, the study quantifies carbon emissions associated with the export of fruits using IPCC-compliant emission coefficients and trade flow data (HS codes 0803–0810). Variables such as GDP per capita, carbon intensity, trade openness, population, tariffs, exchange rate, FDI, and climate agreement memberships (Kyoto and Paris) were included. The results show that trade openness consistently contributes to increased emissions, while WTO membership and Regional Trade Agreements (RTAs) help reduce them. Interestingly, despite their environmental intentions, the Kyoto and Paris agreements were found to be associated with higher emissions, indicating weak enforcement or loopholes in climate accountability in trade. Panel estimators (OLS, FE, PCSE) and Poisson Pseudo-Maximum Likelihood (PPML) models consistently reveal mixed effects of economic and policy variables, reflecting heterogeneity among importing countries. Population and FDI generally reduced emissions, while GDP per capita had varying influences. The study emphasises the need for carbon-conscious trade policies, cleaner logistics, and targeted regulatory mechanisms to reduce emissions from agriculture-based trade. These findings offer policy-relevant insights into balancing trade competitiveness with environmental sustainability, particularly as India continues to expand its agricultural exports in an increasingly carbon-constrained global economy.

Keywords: Trade-embedded emissions, gravity model, Environmental Kuznets Curves, agricultural trade and sustainability, carbon footprint of exports, Indian fruits

JEL codes: C33, F18, Q17, Q54, Q56

I

INTRODUCTION

India is a significant player in global trade, particularly in agricultural products, textiles, pharmaceuticals and services. India's trade patterns reflect its growing economy, large agricultural base, and increasing integration into the global market. In the fiscal year 2022-2023, India's total merchandise trade reached approximately $1.6 trillion, with exports valued at $447 billion and imports at $ 1.1 trillion, representing a significant increase from previous years, driven by robust global demand and recovery from the COVID-19 pandemic. India is one of the world's largest producers and exporters of agricultural products and is vital to the global supply of several key commodities. Also, India is a leading exporter of rice, particularly basmati rice, which accounted for over $10 billion in export value (2022-23). Other significant agricultural exports include turmeric, pepper, cumin, cotton, tea, coffee, sugar and fresh fruits and vegetables. Agricultural exports from India were valued at approximately $50 billion in 2022-2023, which is around 11 per cent

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of India's total merchandise exports, highlighting the importance of agriculture in India’s trade portfolio (UNCOMTRADE, 2023). The major export destinations for Indian agricultural products include the Middle East countries, the United States of America, the European Union, Southeast Asia, and Africa. The United Arab Emirates, Saudi Arabia and Iran are the major importers of Indian rice and other cereals.

Despite benefits, global agricultural trade has also posed challenges, including environmental concerns and trade imbalances. The extensive transportation of agricultural commodities has contributed to increased carbon emissions, raising concerns about the sustainability of this practice. The carbon budget to limit warming to 1.5°C with a 50% chance was rapidly depleting, with only about 250 billion tonnes of CO_2 remaining at the beginning of 2024. Emissions from crop production primarily arose from land-use change, synthetic fertilisers, water management, and energy use for machinery and transportation. Emissions can also vary significantly by region due to differences in agricultural practices, climate and land-use patterns, i.e. country-specific production systems.

The Environmental Kuznets Curve (EKC) theory, originally developed by Grossman and Krueger (1991), posited an inverted U-shaped relationship between per capita income and environmental degradation. The EKC suggested that at low-income levels, economic growth exacerbated environmental degradation due to the intensive use of natural resources. As income increases, societies would become more capable of investing in cleaner technologies and enforcing environmental regulations, leading to a decline in environmental harm. Critics of the EKC, *as cited by* Dinda (2004) and Suri and Chapman (1998), argue that the relationship between income and environmental degradation is not as clear-cut, particularly in agriculture, where technological advancements can either reduce or exacerbate environmental damage depending on their implementation. For instance, while trade had introduced energy-efficient technologies, it might also have encouraged land-use changes that increase emissions.

Fruits and vegetables were essential components of the agricultural trade and carry emissions related to water use, fertilisers and transportation. Garnett (2006) noted that while these crops typically have lower carbon emissions than meat, the energy costs associated with their transportation, especially under refrigerated conditions, can be significant. For fruits and vegetables, improving logistics and cold chain efficiency was key to reducing emissions. Van Hauwermeiren *et al.* (2007) suggested that utilising energy-efficient technologies for storage and transportation could reduce the carbon footprint of exported horticultural products. Investing in renewable energy sources for irrigation and post-harvest handling would also contribute to emissions reductions.

The interaction between trade and environment was often explained through scale, composition and technique effects (Antweiler *et al.*, 2001). These effects illustrate how trade-induced changes can impact carbon emissions: Scale Effect - Trade openness expands economic activities, thereby increasing the demand for agricultural products and natural resources. In India, this was evident in the rise of commercial farming and the increased use of chemical inputs, leading to higher emissions from the agricultural sector (Ghosh, 2010). Composition Effect: Trade openness altered the structure of the economy. If a country like India specialises in agriculture-intensive exports, emissions might increase due to land-use changes and the carbon-intensive nature of agricultural production. Earlier, Ferng (2003) emphasised that developed countries benefited economically from importing carbon-intensive products without accounting for emissions. It argued for equitable emission accounting frameworks. It also criticised the Kyoto Protocol for overlooking emissions from consumption. The work was foundational in exploring trade-environment links from a global justice perspective. Its policy relevance remained strong in carbon accounting debates.

Evidently, Copeland and Taylor (2004) found that trade liberalisation in agriculture led to shifts toward high-emission agricultural activities, such as livestock production. Technique Effect: Trade might lead to cleaner production methods by facilitating access to environmentally friendly technologies. Dean (2002) found that trade-induced access to energy-efficient technologies led to a reduction in carbon emissions in the agricultural sector of developing countries, including India.

The present study will focus on the total fruits exported from India to its export destinations. The time frame for this study will span the past three decades, allowing for an examination of trends and changes in trade patterns and emissions over time. Additionally, the study relies on emission quantification models that may involve certain assumptions and simplifications, which could affect the accuracy of the results. The panel data analysis focused on fruit exports from India and its major exporting destinations.

II

DATA AND METHODOLOGY

2.1 Data and sources

Data sources for emission quantification represent a critical methodological component integrating multiple high-resolution global repositories. Primary sources include the Intergovernmental Panel on Climate Change (IPCC) emission databases, national greenhouse gas inventories, the United Nations Framework Convention on Climate Change (UNFCCC) reporting mechanisms, the Food and Agriculture Organisation (FAO), Our World in Data, and specialised scientific repositories such as the Global Carbon Project and the Carbon Monitoring System.

TABLE 1. DESCRIPTION OF THE VARIABLES AND DATA SOURCES

Variable	Description of variable	Unit	Data sources
$lnEmi_{ijt}$	Natural logarithm of trade (export) embedded carbon emissions between *'i'* and *'j'* in time *'t'*,	Kt CO_2 eqv.	FAOSTAT & literature-derived data
$lnCI_{jt}$	Natural logarithm of carbon emissions intensity of *'j'* in time *'t'*,	%	IPCC framework & literature-derived data
$lnGDPpc_{jt}$	Natural logarithm of GDP per capita of *'j'* in time *'t'*,	$ (2015 constant)	WDI, World Bank data
WTO_{jt}	Binary variables that take the value 1 if *'j'* countries have membership in the WTO and 0 otherwise,	Dummy variable	WITS
RTA_{jt}	Binary variables that take the value 1 if *'j'* countries have membership in RTA and 0 otherwise,	Dummy variable	TRAINS, WITS
$Kyoto_{jt}$	Binary variables that take the value 1 if *'j'* countries have membership in Kyoto and 0 otherwise,	Dummy variable	IPCC
$Paris_{jt}$	Binary variables that take the value 1 if *'j'* countries have membership in the Paris protocol and 0 otherwise,	Dummy variable	IPCC
TOI_{it}	Trade Openness Index of the selected commodity of *'i'* country,	%	UNCOMTRADE
$lnPop_{jt}$	Natural logarithm of population of *'j'* in time *'t'*,	Million	WDI, World Bank data
$lnTR_{jt}$	Natural logarithm of tariff rate of *'j'* in time *'t'*,	%	TRAINS, WITS
$lnFDI_{jt}$	Natural logarithm of foreign direct investment (inflows) of *'j'* in time *'t'*,	Against $ (2015 constant)	WDI, World Bank data
$lnER_{jt}$	Natural logarithm of the exchange rate of *'j'* in time *'t'*,	Against $ (2015 constant)	WDI, World Bank data
$lnInfR_{jt}$	Natural logarithm inflation rate of *'j'* in time *'t'*	Against $ (2015 constant)	WDI, World Bank data
u_{it}	Error term, which is assumed to be normally distributed with zero mean and constant variance for all observations, and to be uncorrelated		

These sources provide comprehensive emissions data across various sectors, incorporating detailed information on industrial processes, agricultural activities, energy production, and transportation systems. Complementary data sources include national statistical offices, international organisations such as the World Bank and OECD, and sector-specific emission tracking platforms. The data on fruit exports from India and its major exporting destinations were collected for the period from

1990 to 2022 for analysis under the HS codes, *specifically* HS 0803-0810. The annual secondary data were collected from the UN COMTRADE, UN-FAOSTAT, the World Bank database and APEDA (India). The variables used in the analyses, along with their corresponding data sources, are tabulated in Table 1, along with the expected signs, as shown in Table 2.

TABLE 2. STUDY VARIABLES WITH SIGNS EXPECTED

Independent variables	Expected signs	Sources
Natural logarithm of carbon emissions intensity of *'j'* in time *'t'* ($lnCI_{jt}$)	+/-	Qayyum *et al.* (2021)
Natural logarithm of GDP per capita of *'j'* in time *'t'* ($lnGDPpc_{jt}$)	+	Jagdambe and Kanna (2020)
Trade Openness Index of the selected commodity of *'i'* country (TOI_{it})	+	Can *et al.* (2022)
Natural logarithm of population of *'j'* in time *'t'* ($lnPop_{jt}$)	+	Jagdambe and Kanna (2020)
Natural logarithm of tariff rate of *'j'* in time *'t'* ($lnTR_{jt}$)	-	Yean and Yi (2014) and Singh *et al.* (2021)
Natural logarithm of foreign direct investment (inflows) of *'j'* in time ($lnFDI_{jt}$)	+	Tiwari and Mutascu (2011)
Natural logarithm of exchange rate of *'j'* in time *'t'* ($lnER_{jt}$)	+/-	De Grauwe (1988) and Aslan *et al.* (2021)
Natural logarithm of inflation rate of *'j'* in time *'t'* ($lnInfR_{jt}$)	+/-	Aslan *et al.* (2021)
Binary variables that take the value 1 if *'j'* countries have membership in WTO/RTA/Kyoto/Paris and 0 otherwise	+/-	Balogh and Mizik. (2023)

2.2 Methodology

The IPCC standards provided a reliable and straightforward accounting approach for calculating GHG emissions from regional systems on an annual basis. The IPCC guidelines propose three tiers (levels of information) for calculating GHG emissions based on available data. In the Carbon Emission Accounting Framework, the Life Cycle Assessment (LCA) model provides comprehensive approaches for estimating emissions across different stages, including production, processing, transportation, and final consumption. The carbon footprint (CF) of crop production was evaluated by calculating the greenhouse gas (GHG) emissions generated from agricultural inputs, machinery operations, and other cultivation activities throughout the entire crop production process, with the results quantified and reported in carbon equivalent (CE) units (Hillier *et al.*, 2009). The carbon intensity of exported fruits also varied depending on the mode of transport (road, rail or maritime), with longer distances adding to the embedded carbon footprint. By integrating trade data from India's Directorate General of Commercial Intelligence and Statistics (DGCI&S) with emission factors from IPCC guidelines, a systematic quantification of carbon emissions from agricultural exports could be achieved. This assessment provided insights into potential low-carbon trade strategies, including adopting sustainable agricultural practices, improving supply chain efficiency, and promoting carbon-conscious trade policies.

Emission = Activity Data * Emission Factor

Panel data is a dataset that comprises the behaviour of each individual or object and is monitored over time. The observations used in the study are consistent across all variables and years. As a result, unbalanced panel datasets were defined. And the omitted variables are defined as those that cannot be observed or measured using panel data. Tinbergen (1962) first applied the model to international trade, and Linneman (1966) related that the trade flows between two countries are proportional to the GDP of each country divided by the distance between their respective economic centres - usually the distance between their capital cities. Thus, it has been postulated that the trade flow between the two countries is directly proportional to their income and inversely proportional to the distance between them, which serves as a proxy for trade costs (Khurana and Nauriyal, 2017).

The present study employed the gravity model to examine the impact of the trade door to the Free Trade Agreement between India and its trading partners from 1990 to 2022, using panel data. Many empirical studies, such as those by Wang and Winters (1991), Hamilton and Winters (1992), Brulhart and Kelly (1999), and Nilsson (2000), used cross-sectional data to analyse the effect of trade. However, the exploitation of country heterogeneity was made possible by the use of panel data; hence, Serlenga and Shin (2007), Khurana and Nauriyal (2017) and Jagadambe and Kannan (2020) employed panel data extensively.

The basic model used in gravity analysis is multiplicative; therefore, the natural logarithm was employed to obtain a linear relationship between the variables and the equations.

$$\begin{aligned} lnEmi_{ijt} = {} & \beta_1 + \beta_2(lnCI_{jt}) + \beta_3(lnGDPpc_{jt}) + \beta_4(WTO_{jt}) + \beta_5(RTA_{jt}) \\ & + \beta_6(Kyoto_{jt}) + \beta_7(Paris_{jt}) + \beta_8(TOI_{it}) + \beta_9(lnPop_{jt}) \\ & + \beta_{10}(lnTR_{jt}) + \beta_{11}(lnFDI_{jt}) + \beta_{12}(lnER_{jt}) \\ & + \beta_{13}(lnInflation_{jt}) + u_{it} \end{aligned}$$

A difficulty arises when zero trade flow is estimated, *i.e.*, the log-log model is not valid, when $X_{ij} < 0$. However, excluding zero-value observations poses significant issues because it eliminates vital information on low levels of trading (Eichengreen and Irwin, 1998). Results might be biased, especially if zero trade flows are not distributed randomly (Burger *et al.*, 2009). The problem of heterogeneity results in biased and inconsistent model estimates because of the invariant variable of distance and the dummy variable of FTA. Hence, for the problem of zero trade flow and heterogeneity, Baier and Bergstrand (2007) recommended the use of country and time fixed effects simultaneously in a panel data analysis to obtain unbiased estimates from the gravity equation, while, Silva and Tenreyro (2006) suggested Poisson Pseudo-Maximum Likelihood (PPML) as a robust estimator that addresses the heteroscedasticity problem and measurement errors. Even Fally (2015) suggested that the PPML model, which is structurally consistent with importer and exporter fixed effects, is suitable for appropriate estimation.

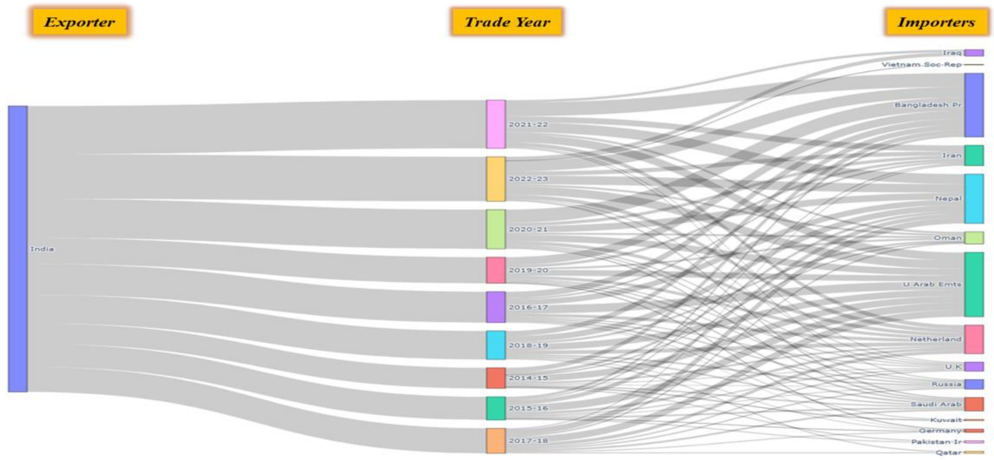
Considering the problem of zero trade and heteroscedasticity, the PPML method is widely used to estimate the gravity model. Several studies, such as Sun and Reed (2010), Silva and Tenreyro (2006), Khurana and Nauriyal (2017), and Jagdame and Kannan (2020), have used the PPML method to analyse trade creation and trade diversion resulting from FTA. The endogeneity and zero trade flow problems were addressed in the present study by using fixed effects in a panel setting. The fixed effects of only country and time, as well as the country effect, were analysed. The bias of omitted variables would be eliminated in the fixed model due to the exclusion of unobserved variables that are either evolving or constant across entities. Country-specific fixed effects were modelled as country-specific intercepts that were not dependent on time.

III

RESULTS AND DISCUSSION

3.1 Trade-embedded emissions in the Indian fruit exports

The majority of the trading countries in the study referred to the top export destinations of Indian fruit exports. The selected top Indian export destinations for the panel data model accounted for 77 per cent of India's fruit exports. GHG emissions are quantified across the entire production process, including the supply chain and exports to various destinations, both within and outside India. Hence, the trade-embedded carbon leakages are analysed using a panel data model. In the analysis of Indian fruit export emissions using panel estimators (Ordinary Least Squares (OLS), Fixed Effects model (FE), and Panel Corrected Standard Error model (PCSE)), the estimated coefficients revealed how key independent variables influenced the trade-embedded carbon emissions, and the results are presented in Table 3. The panel countries chosen for the analysis were selected based on their consistent Indian fruit imports over the years, *namely* Bangladesh, Iran, Nepal, the Netherlands, the United Arab Emirates, and the United Kingdom. Furthermore, the trade flow is depicted in Figure 1.



Source: APEDA (2024)

FIGURE 1. MAJOR EXPORT DESTINATIONS OF INDIAN FRUITS (HS 0803-0810)

3.2 Panel data analysis for trade-embedded emission in the Indian fruit exports

The carbon intensity of India's GDP exhibited a positive but statistically insignificant effect in the OLS and FE models, while the PCSE model showed a significant positive relationship (López *et al.*, 2018; Weber and Matthews, 2007). A percentage increase in India's carbon intensity was associated with a 0.368 percentage point rise in emissions under the PCSE model, indicating that emission-intensive production contributed to higher trade-embedded emissions in fruit exports. However, the FE model produced a negative but insignificant coefficient, suggesting that the relationship varied across different model specifications. India's GDP per capita had a mixed effect. The OLS model showed an insignificant positive effect, while the FE and PCSE models reported statistically significant positive relationships. In the FE model, a percentage increase in GDP per capita led to a 1.49 percentage point rise in emissions, indicating that economic growth contributed to higher emissions from fruit exports (Xu and Dietzenbacher, 2014; Su and Ang, 2014). The PCSE model confirmed the same with a 0.58 per cent increase.

Conversely, the GDP per capita of importing countries showed a weak negative effect in the OLS and PCSE models. Still, it was positive and marginally significant in the FE model, suggesting that wealthier importing countries might not necessarily impose stricter environmental controls on fruit imports. Trade policy variables showed significant effects. WTO membership of importing countries consistently reduced trade-embedded emissions across all models (Shapiro, 2021; Frankel and Rose, 2005). The FE model showed the strongest effect, where WTO membership was associated with a 1.438 per cent reduction in emissions. Similarly, regional RTA had a negative but insignificant effect in the PCSE model, implying that RTAs did not significantly influence emissions reductions. Contrary to expectations, international climate commitments, such as the Kyoto Protocol and the Paris Agreement, have had significant positive effects on trade-embedded emissions. Kyoto Protocol membership increased emissions by 1.814 per cent (OLS), 2.915 per cent (FE), and 2.490 per cent (PCSE), suggesting that signatory countries continued to import carbon-intensive fruits despite their commitments.

TABLE 3. CARBON LEAKAGE IN INDIAN FRUITS EXPORTS (HS 0803-0810): OLS, FE AND PCSE ESTIMATION

Dependent variable: Trade embedded emission from Indian fruits exports ($lnEmi_{ij}$)
Data: 1990-2022

Variable	OLS			FE			PCSE		
	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value
$lnCO_2intensityg$									
dp_j	0.366	0.266	0.174	-0.219	0.250	0.384	0.36***	0.077	0.000
$lngdppc_i$	0.313	0.249	0.213	1.49***	0.319	0.000	0.58***	0.145	0.000
$lngdppc_j$	-0.020	0.017	0.240	0.74*	0.390	0.062	-0.209**	0.087	0.017
wto_j	-0.79***	0.203	0.000	-1.438**	0.348	0.000	-1.04***	0.062	0.000
rta_j	-1.85***	0.243	0.000	-	-	-	-0.563	0.521	0.280
$kyoto_j$	1.81***	0.228	0.000	2.91***	0.276	0.000	2.49***	0.073	0.000
$paris_j$	0.51***	0.154	0.002	0.268**	0.119	0.028	0.36***	0.050	0.000
toi_{ij}	0.62***	0.094	0.000	0.62***	0.069	0.000	0.48***	0.036	0.000
$lntariff_j$	0.024	0.065	0.714	0.043	0.045	0.346	0.053**	0.022	0.016
$lnpop_j$	0.193*	0.109	0.081	-12.79 ***	2.043	0.000	0.27***	0.032	0.000
$lnfdi_j$	-0.036	0.040	0.379	0.030	0.036	0.402	-0.057***	0.012	0.000
$lnexrate_j$	-0.149**	0.067	0.031	1.01***	0.218	0.000	-0.28***	0.077	0.000
$lninflation_j$	0.134*	0.075	0.077	0.069	0.054	0.205	0.012	0.045	0.797
Intercept	4.449	2.828	0.120	212.1***	32.167	0.000	0.026*	1.131	0.073
R-square		0.932			0.929			0.994	
No. of observations		80			80			80	
Panel countries		6			6			6	
RESET values	F(13,66) = 69.17 Prob > F = 0.0000			F(12,62) = 67.11 Prob > F = 0.0000 corr(u_i, X_b) = -0.9968 u_i = 0; F(5, 62) = 40.24			Wald $chi^2(13)$ = 11152.86 Prob > chi^2 = 0.0000		

*indicates p<0.10, **indicates p<0.05, *** indicates p<0.01

Paris Agreement membership also exhibited a similar trend, increasing emissions across all models. The trade openness index of India consistently showed a strong positive effect on emissions, with coefficients of 0.621 (OLS), 0.628 (FE), and 0.487 (PCSE), indicating that greater trade openness contributed to higher emissions in fruit exports (Antweiler *et al.*, 2001). Import tariffs showed an insignificant effect in the OLS and FE models. Still, they had a small positive effect in the PCSE model, suggesting that tariff reductions alone did not have a significant impact on emissions.

Demographic and economic variables influenced the patterns of emissions. The population of the importing country had a mixed effect. In the FE model, it showed a strong negative impact (-12.79%), indicating that larger populations in importing countries were associated with lower emissions, possibly due to higher demand for domestic production (Du *et al.*, 2011). However, the OLS and PCSE models found positive effects, with the PCSE model showing a significant increase of 0.277%. FDI had an insignificant effect in the OLS and FE models but a small negative impact (-0.057%) in the PCSE model, suggesting that FDI might contribute to cleaner production methods. The exchange rate had contrasting effects across models, with the OLS and PCSE models exhibiting a negative relationship. In contrast, the FE model showed a strong positive relationship, suggesting that currency depreciation may have complex effects on emissions (Li and Hewitt, 2008).

Using the PPML approach, the study further analysed trade-embedded emissions from Indian fruit exports under three specifications: time effects only, country effects only, and both effects combined. The results are presented in Table 4. The carbon intensity of India's GDP showed mixed results, with a positive effect in the time-effects-only model (0.064%) and both-effects model (0.079%), but a negative and insignificant effect in the country effects-only model. India’s GDP per capita had an insignificant effect in most PPML specifications, except in the country effects only model, where it showed a significant positive impact (0.26%). The GDP per capita of importing countries had a weak negative effect in the time effects only and both effects models, but was significantly positive (0.227%) in the country effects only model, indicating that economic growth in importing countries could sometimes contribute to higher emissions. Trade policy variables retained their significance in PPML models. WTO membership had a negative impact on emissions across all specifications, with the strongest reduction observed in the country effects only model (-0.412%). Regional trade agreements had a substantial negative effect on the country effects model (-3.629%), but a smaller, significant negative effect in the time effects model and the combined effects model. Kyoto Protocol and Paris Agreement commitments increased emissions in all PPML models, reinforcing the earlier findings that, despite climate commitments, importing countries continued to drive carbon-intensive trade in fruits.

Trade openness had a positive influence on emissions across all PPML models, while import tariffs had no significant effect. The importing country population exhibited a significant negative effect in the country-effects-only model (-2.98%) but was insignificant in the other two specifications. Exchange rate fluctuations also had varying effects, with the time effects only and both effects models showing a negative impact, while the country effects only model indicated a positive effect.

TABLE 4. CARBON LEAKAGE IN INDIAN FRUITS EXPORTS (HS 0803-0810): PPML ESTIMATION

Dependent variable: Trade embedded emission from fruits exports ($lnEmi_{ij}$)
Data: 1990-2022

Variable	PPML (Time effect only)			PPML (Country effect only)			PPML (Both effects)		
	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value	Coef.	Std. Err.	p-value
$lnCO_2intensitygdp_j$	0.064*	0.033	0.054	-0.071	0.044	0.105	0.079**	0.035	0.025
$lngdppc_i$	-0.091	0.149	0.545	0.26***	0.056	0.000	0.024	0.032	0.461
$lngdppc_j$	-0.002	0.002	0.267	0.22***	0.073	0.002	-0.004	0.003	0.127
wto_j	-0.107**	0.048	0.028	-0.41***	0.074	0.000	-0.101	0.062	0.104
rta_j	-0.29***	0.063	0.000	-3.62***	0.631	0.000	-0.29***	0.072	0.000
$kyoto_j$	0.320**	0.133	0.017	0.69***	0.092	0.000	0.34***	0.133	0.010
$paris_j$	0.119***	0.039	0.003	0.035*	0.019	0.065	0.078***	0.024	0.002
toi_{ij}	0.083***	0.028	0.003	0.11***	0.017	0.000	0.105***	0.034	0.002
$lntariff_j$	0.002	0.008	0.746	0.002	0.006	0.776	-0.001	0.009	0.873
$lnpop_j$	0.028	0.019	0.141	-2.98***	0.569	0.000	0.027	0.020	0.172
$lnfdi_j$	-0.009	0.006	0.144	0.005	0.005	0.309	-0.013	0.009	0.178
$lnexrate_j$	-0.03***	0.009	0.001	0.21***	0.0533	0.000	-0.03***	0.009	0.003
$lninflation_j$	0.033**	0.015	0.028	0.013	0.010	0.213	0.021	0.017	0.225
Intercept	2.43*	1.337	0.069	54.05***	9.871	0.000	1.77***	0.642	0.006
R-square	0.051			0.053			0.048		
No. of observations	80			80			80		
Panel countries	6			6			6		
RESET values	Pesudo log-likelihood = -155.680			Pesudo log-likelihood = -155.456			Pesudo log-likelihood = -156.192		
				Wald $Chi^2(17) = 3791.06$			Wald $Chi^2(13) = 369.97$		
				Prob> $Chi^2 = 0.000$			Prob> $Chi^2 = 0.000$		

* indicates p<0.10, ** indicates p<0.05, *** indicates p<0.01

Datasets were analysed for two periods, i.e. Pre-2005 and Post-2005, as most of the RTAs and climate-related commitments were signed during the mid-2000s. From Table 5, it could be noted that before 2005, trade-embedded emissions from Indian fruit exports were significantly reduced by regional trade agreements (RTAs), while trade openness (TOI) led to an increase. The Kyoto Protocol had a weak but positive effect, and GDP per capita in importing countries showed no significant impact. After 2005, RTAs continued to mitigate emissions, while WTO membership contributed to a reduction (Zhang *et al.*, 2017). The Paris Agreement and trade openness played a more prominent role in influencing emissions, while import tariffs had a minor but significant positive effect.

TABLE 5. CARBON LEAKAGE IN INDIAN FRUITS EXPORTS (HS 0803-0810): PANEL ANALYSIS FOR PRE-2005 AND POST-2005

Dependent variable: Trade embedded emission from Indian fruits exports ($lnEmi_{ij}$)
Data: 1990-2022

Variable	Pre-2005				Post-2005			
	OLS		PPML		OLS		PPML	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
$lnCO_2intensitygdp_j$	-0.304	0.395	-0.121*	0.060	-0.1647	0.157	-0.0218	0.088
$lngdppc_i$	-0.853	0.279	-0.432**	0.015	0.158	0.598	0.017	0.562
$lngdppc_j$	-	-	-	-	-	-	-	-
wto_j	0.097	0.740	0.055	0.292	-0.44**	0.045	-0.05**	0.041
rta_j	-3.86***	0.000	-0.74***	0.000	-1.63***	0.000	-0.25***	0.000
$kyoto_j$	0.453	0.185	0.10*	0.055	1.23***	0.000	0.178	0.248
$paris_j$	-	-	-	-	0.45***	0.004	0.06***	0.002
toi_{ij}	1.23***	0.000	0.29***	0.000	0.55***	0.000	0.07***	0.000
$lntariff_j$	-0.047	0.470	-0.032**	0.019	0.11**	0.032	0.01***	0.001
$lnpop_j$	-	-	-	-	-	-	-	-
$lnfdi_j$	0.012	0.716	-0.011	0.221	0.042	0.322	0.005	0.204
$lnexrate_j$	-	-	-	-	-	-	-	-
$lninflation_j$	-	-	-	-	-	-	-	-
Intercept	18.29***	0.006	6.08***	0.000	7.79***	0.001	2.06***	0.000
R-square	0.99		0.106		0.878		0.023	
No. of observations	19		19		67		67	
Panel countries	6		6		6		6	
RESET values	F(8,10)=123.16 Prob>F=0.000		Pseudo log-likelihood = -35.663 Wald $Chi^2(8)$ = 18985.54 Prob> Chi^2 = 0.000		F(9,57)=45.85 Prob>F=0.00		Pseudo log-likelihood = -131.793 Wald $Chi^2(9)$ = 322.85 Prob> Chi^2 = 0.000	

* indicates p<0.10, ** indicates p<0.05, *** indicates p<0.01

IV

CONCLUSION

We have analysed the panel dataset of Indian fruit exports with its trading partners (export destinations) to examine the influence of the select variables on trade (exports) embedded emissions over the years using different econometric models. Our econometric study results show a statistically significant association between the production and exports of fruits and GHG emission rates. The findings showed that the higher GDP per capita in India increased emissions, while trade openness also contributed to higher carbon intensity in Indian fruit exports. WTO and regional trade agreements helped reduce emissions, whereas ratification of the Kyoto and Paris Agreements was linked to increased emissions, likely due to stricter reporting requirements. FDI had mixed effects, sometimes lowering emissions through the adoption of cleaner technologies.

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