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Global Value Chains and Decarbonization: A Firm-Level Threshold Evidence from India

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Global Value Chains and Decarbonization: A Firm-Level Threshold Evidence from India

Abstract

Do global value chains (GVCs) make firms cleaner, and under what conditions? Leveraging rich firm-level data from India in the period of 2010–2024, this study investigates the impact of GVC participation on firms' environmental performance. To address dynamics and heterogeneous responses, we estimate dynamic panel threshold regressions with firm growth as the regime variable. We find that GVC participation raises energy and carbon intensity for low-growth firms, but reduces both—and increases renewable energy use—for high-growth firms. Channel decomposition shows that forward participation delivers the clearest efficiency and decarbonization gains in the high-growth regime, while backward participation improves energy efficiency at high growth yet exhibits mixed carbon effects; in the low-growth regime, forward linkages raise intensity whereas backward linkages are comparatively less harmful or even carbon-reducing. This paper underscores the capacity-dependence of trade integration's environmental impact and shows that policy can shift the relevant margin through finance, R&D, and compliance infrastructure.

Keywords: Global Value Chain; Forward linkage; Backward linkage; Energy intensity; Carbon emissions; Renewable energy consumption; Dynamic panel threshold regression

JEL Classification: F14, F15, F18, Q42, Q56

1 Introduction

Do global value chains (GVCs) make firms cleaner, and under what conditions—and through which channels? We revisit this question by shifting the focus from average effects to the firm-level capacity margin at which international integration turns from dirty to clean. The salience of the question is immediate for India: a rapidly industrializing economy, the world's third-largest energy user and a major emitter of CO_2 (Ahmed et al., 2022; Huang et al., 2021; Methmini et al., 2025), and a country increasingly embedded in globally fragmented production (Meng et al., 2018; Yan et al., 2020). Trade in intermediates accounts for more than half of world trade (World Bank, 2020); GVCs can promote growth via technology transfer and spillovers (Humphrey & Schmitz, 2002; Pietrobelli & Rabellotti, 2011), yet participation is uneven and often confines developing-country firms to low value-added segments (S. Wang et al., 2021). Whether, and for whom, GVC integration improves environmental performance therefore remains an empirical question.

We construct a balanced panel of 143 listed Indian manufacturing firms for 2010–2024. We harmonize firm-reported, fuel-specific physical energy into a common unit and compute firm-level CO_2 using standard emission factors. GVC participation is measured at the firm level and disaggregated into *forward* (exports over sales) and *backward* (imported-input intensity) linkages. To capture dynamics and heterogeneity, we estimate dynamic panel threshold regressions with firm growth as the regime variable, formally testing for nonlinearity and complementing with alternative instruments and system-GMM robustness. This design speaks directly to a literature that has been predominantly country-level and linear (Liu & Zhao, 2021; S. Wang et al., 2022), while a smaller set of firm-level studies remains context-specific (Lee & Wen, 2025; Zhang et al., 2021; Zheng et al., 2022); for India, related work has examined energy efficiency, foreign demand shocks, and regulatory interventions such as the Perform, Achieve and Trade (PAT) scheme (Bagchi et al., 2022; Balachandra et al., 2010; Barrows & Ollivier, 2021; Oak & Bansal, 2022; Pal et al., 2024; Roy & Yasar, 2015).

We find a pronounced growth threshold that flips the sign of environmental impacts.

Below the threshold, greater GVC participation raises energy and carbon intensity and dampens renewable uptake. Above it, GVC participation reduces both intensities and increases renewable energy use. Channel decomposition shows that forward participation delivers the clearest efficiency and decarbonization gains in the high-growth regime, while backward participation improves energy efficiency at high growth but exhibits mixed carbon effects; in the low-growth regime, forward linkages raise intensities whereas backward linkages are comparatively less harmful and, in some specifications, carbon-reducing. These patterns reconcile scale (dirty) versus technique (clean) forces by showing that the latter dominate only once firms possess sufficient growth capacity.

This paper makes four contributions. First, it exploits rich firm-level data from India to examine how participation in global value chains (GVCs) relates to environmental performance, with a focus on energy use and carbon outcomes. We add to the limited firm-level evidence for India by analyzing the effects of GVC participation on energy efficiency, carbon productivity, and renewable energy consumption. Second, it addresses a salient gap by explicitly linking firms' renewable-energy adoption to their position in GVCs, drawing on a uniquely detailed dataset that records a wide spectrum of renewable and non-renewable energy inputs used by Indian manufacturers. Third, it employs a disaggregated measure of GVC participation that distinguishes forward (exports over sales) and backward (imported-input intensity) linkages, allowing channel-specific effects to be identified. Fourth, using firm growth as a threshold variable, it applies a dynamic panel threshold regression to estimate multi-regime effects of GVC participation on energy intensity, carbon intensity, and renewable energy use. This framework captures the key nonlinearities in the trade–environment relationship and provides new evidence on *when* and *through which channels* integration cleans production and *who* benefits.

The remainder of the paper is structured as follows. Section 2 provides theoretical description on a mechanism of state-dependent green technology adoption along GVCs. Section 3 outlines the empirical framework, describes the data sources, details the variable construction, and provides key descriptive statistics of the study. Section 5 presents the empirical results along with robustness checks. Finally, Section 6 concludes the paper and offers key policy implications.

2 Mechanism: State-Dependent Green Technology Adoption along GVCs

In this section, we begin by developing a mechanism of state-dependent green technology adoption along GVCs, structured to anticipate the empirical analysis. First, we define the key objects and measurement conventions—output, fuel-specific energy use, emissions from fixed fuel factors, and GVC participation decomposed into export (forward) and imported-input (backward) exposure. Second, we present a firm decision framework that separates the amount of energy required (driven by efficiency) from the mix of fuels (driven by relative prices). Third, we introduce a capacity threshold: below it, GVC participation mainly scales activity and can worsen energy and carbon intensity; above it, firms upgrade technologies, typically improving intensities and increasing renewables. Fourth, we distinguish forward and backward channels, explaining why they operate through different combinations of scale, composition, and technique. We close by mapping these elements to our threshold-based panel estimators and their testable predictions.

2.1 Environment, Variables, and Notation

We study manufacturing firms $i = 1, \dots, N$ over periods $t = 1, \dots, T$. Output is $y_{it} \in \mathbb{R}_+$. Inputs are capital $K_{it} \in \mathbb{R}_+$, labor $L_{it} \in \mathbb{R}_+$, and a vector of fuel-specific physical energy uses $\mathbf{E}_{it} = (E_{s,it})_{s \in \mathcal{S}} \in \mathbb{R}_+^{|\mathcal{S}|}$, where $\mathcal{S}$ is a finite set of fuels (coal, petroleum products, natural gas, electricity, biomass/solar). Each $E_{s,it}$ is converted into a common heat unit (GJ or kcal).

GVC participation is two-dimensional: $F_{it} \in [0, 1]$ is the export share (Forward exposure), and $B_{it} \in [0, 1]$ is the imported-intermediate/input share (Backward exposure). When a scalar index is useful, write $V_{it} = \mathcal{V}(F_{it}, B_{it})$, where $\mathcal{V} : [0, 1]^2 \to [0, 1]$ is continuous, strictly increasing in each argument, and $\mathcal{V}(0, 0) = 0$. If the raw measure of Backward exposure is not a share, it can be rescaled to $[0, 1]$ without loss of generality.

Energy intensity is

$$EI_{it} \equiv \frac{\sum_{s\in\mathcal{S}} E_{s,it}}{y_{it}}. \tag{1}$$

Carbon intensity is

$$CI_{it} \equiv \frac{CO2_{it}}{y_{it}}, \qquad CO2_{it} = \sum_{s\in\mathcal{S}} EF_s\, E_{s,it}\,, \tag{2}$$

where $EF_s > 0$ is the fuel-specific emission factor in tCO_2 per heat unit (e.g., tCO_2/GJ). In the baseline, $\{EF_s\}$ are exogenous fuel constants; as a robustness check, one may allow $EF_{s,t}$ for electricity to reflect grid variation. Renewables use is $R_{it} \equiv \sum_{s\in\mathcal{S}_{\mathrm{RE}}} E_{s,it}$ for a subset $\mathcal{S}_{\mathrm{RE}} \subset \mathcal{S}$.

Outcomes are built from physical energy by fuel with fixed emission factors; hence any impact of GVCs on CI must operate through how much energy is used and which fuels are chosen—exactly the margins estimated in the empirical section across regimes.

2.2 Technology, Cost Minimization, and Energy Demand

Production satisfies

$$y_{it} = A_{it}\, \Phi(F_{it}, B_{it})\, f\Big(K_{it}, L_{it},\, (1-\lambda(G_{it}))\, \widetilde{E}_{it}\Big), \tag{3}$$

where $A_{it} > 0$ is Hicks-neutral productivity; $f : \mathbb{R}^3_+ \to \mathbb{R}_+$ is C^2, increasing and concave. The function $\Phi : [0,1]^2 \to \mathbb{R}_+$ is positive and C^1, summarizing scale/composition effects of GVC participation. The efficiency map $\lambda : [0,\infty) \to [0,\bar{\lambda})$ is C^1, strictly increasing with $\lambda(0) = 0$ and $\bar{\lambda} \in (0,1)$; an admissible form is $\lambda(G) = \bar{\lambda}\big(1 - e^{-\kappa G}\big)$ with $\kappa > 0$. Green process capital $G_{it} \in \mathbb{R}_+$ captures process upgrades (high-efficiency equipment, waste-heat recovery, EMS, renewable PPAs/on-site).

Energy services are aggregated via a CES index,

$$\widetilde{E}_{it} = \Big(\sum_{s\in\mathcal{S}} \omega_s\, E^{\rho}_{s,it}\Big)^{1/\rho}, \qquad \rho \in (-\infty, 1) \setminus \{0\}, \quad \sum_s \omega_s = 1,\ \omega_s > 0, \tag{4}$$

with elasticity of substitution $\sigma = 1/(1-\rho)$. Let $P_E(\mathbf{p}_t)$ be the energy price index dual to Eq. (4), depending only on fuel prices $\mathbf{p}_t = (p_{s,t})_{s\in\mathcal{S}}$ and $\{\omega_s\}$. Cost minimization under Eq. (3) implies

$$E_{it}^{\text{tot}} \equiv \sum_s E_{s,it} = E\big(P_E(\mathbf{p}_t),\, y_{it};\, \lambda(G_{it})\big), \qquad \frac{\partial E}{\partial P_E} < 0,\ \frac{\partial E}{\partial y} > 0,\ \frac{\partial E}{\partial \lambda} < 0, \tag{5}$$

and fuel shares

$$\pi_{s,\,it} \equiv \frac{E_{s,it}}{E_{it}^{\text{tot}}} = \pi_s\Big(\frac{p_{s,t}}{P_E(\mathbf{p}_t)},\, \omega_s;\, \sigma\Big) \in (0,1), \qquad \sum_s \pi_{s,\,it} = 1, \tag{6}$$

which depend only on relative prices and CES parameters (not on λ). Efficiency $\lambda(G)$ reduces the amount of energy required per effective unit; prices determine which fuels are chosen. If one wishes to let efficiency also affect composition, this can be modeled by $\omega_s = \omega_s(G)$, but the baseline keeps $\{\omega_s\}$ fixed for identification clarity.

Eqs. (5) and (6) explain the signs in the regressions: GVCs affect EI, CI, R by shifting Φ and λ. If λ does not move (low capacity), GVCs mainly scale up activity; if λ moves (high capacity), energy needs fall and the mix tilts cleaner. This is the intuition behind the regime-dependent coefficients we estimate.

2.3 Lumpy Upgrading and a Capacity Threshold

Green capital evolves as

$$G_{i,t+1} = (1-\delta_G)G_{it} + I_{it}^G, \qquad \delta_G \in (0,1), \tag{7}$$

with a fixed installation cost $\mathcal{F} > 0$ and an adjustment cost $C : [0,\infty) \to [0,\infty)$ that is C^2, increasing and convex, $C(0) = 0$. Let $g_{it} \in \mathbb{R}_+$ denote organizational/financial capacity (proxied empirically by firm growth). Define the present value of benefits as

$$\mathcal{B}(V_{it}, g_{it}) = \mathbb{E}_t \sum_{\tau \geq t} \beta^{\tau-t}\Big[\mathcal{S}\big(P_E(\mathbf{p}_\tau), y_{i\tau}; \lambda(G_{i\tau})\big) + \mathcal{C}\big(EF, \pi_{s,i\tau}, E_{i\tau}^{\text{tot}}\big) + \mathcal{Q}\big(\Phi(F_{i\tau}, B_{i\tau})\big)\Big], \tag{8}$$

with $\beta \in (0,1)$, where $\mathcal{S}, \mathcal{C}, \mathcal{Q}$ are continuous and increasing in their arguments (fuel-cost savings, broad carbon-related compliance/penalty avoidance, and quality/standards premia). Assume $\partial\mathcal{B}/\partial V > 0$, $\partial\mathcal{B}/\partial g > 0$, and a monotone single-crossing property in (V, g). Then there exists a capacity threshold $g^\star \in \mathbb{R}_+$ such that

$$I_{it}^G = \begin{cases} I^\star(V_{it}, g_{it}) & \text{if } g_{it} \geq g^\star, \\ 0 & \text{if } g_{it} < g^\star, \end{cases} \qquad \text{with } I^\star \text{ non-decreasing and continuous.} \tag{9}$$

To discipline signs in low capacity, adopt the explicit short-run scale assumption that, with λ effectively fixed and partial factor adjustment, the short-run energy–output elasticity exceeds one:

$$\text{Assumption SR:} \qquad \varepsilon_{E^{\text{tot}},y}^{SR} \equiv \frac{\partial \ln E^{\text{tot}}}{\partial \ln y}\Big|_{\lambda \text{ fixed}} > 1. \tag{10}$$

If $g_{it} < g^\star$ (low capacity), GVCs primarily expand scale: E^{tot} rises more than proportionally to y by Eq. (10), so EI and CI increase, while R can decline. If $g_{it} \geq g^\star$ (high capacity), upgrading activates: $\lambda(G)$ increases, the energy required per effective unit falls, and the mix tilts toward low-carbon sources; thus EI and CI decrease and R increases. These are the sign patterns the DPTR will test by comparing coefficients below vs. above the growth-based threshold γ.

2.4 Forward vs Backward: Channel Heterogeneity and S–C–T Mapping

Forward exposure F_{it} (export orientation) and Backward exposure B_{it} (imported intermediates/equipment) operate through distinct channels and may feature different effective thresholds $g_F^\star$ and $g_B^\star$. For Forward, export expansion enlarges markets (scale), tightens external quality/ESG standards and learning-by-exporting (technique), and may tilt product/process composition (composition). For Backward, access to imported intermediates/equipment can also scale production but more directly enables efficient/low-carbon upgrading; integration demands can make its threshold differ.

A qualitative decomposition for marginal effects is

$$\frac{\partial EI}{\partial F} = S_F(F_{it};\theta) + C_F(F_{it};\theta) - T_F(F_{it};\theta)\,\mathbf{1}\{g_{it} \geq g_F^\star\}, \tag{11}$$
$$\frac{\partial CI}{\partial F} = S_F'(F_{it};\theta) + C_F'(F_{it};\theta) - T_F'(F_{it};\theta)\,\mathbf{1}\{g_{it} \geq g_F^\star\}, \tag{12}$$
$$\frac{\partial R}{\partial F} = T_F^R(F_{it};\theta)\,\mathbf{1}\{g_{it} \geq g_F^\star\} + C_F^R(F_{it};\theta), \tag{13}$$

and, analogously, for Backward

$$\frac{\partial EI}{\partial B} = S_B(B_{it};\theta) + C_B(B_{it};\theta) - T_B(B_{it};\theta)\,\mathbf{1}\{g_{it} \geq g_B^\star\}, \tag{14}$$
$$\frac{\partial CI}{\partial B} = S_B'(B_{it};\theta) + C_B'(B_{it};\theta) - T_B'(B_{it};\theta)\,\mathbf{1}\{g_{it} \geq g_B^\star\}, \tag{15}$$
$$\frac{\partial R}{\partial B} = T_B^R(B_{it};\theta)\,\mathbf{1}\{g_{it} \geq g_B^\star\} + C_B^R(B_{it};\theta). \tag{16}$$

Here $\theta \equiv (\{\omega_s\}, \sigma)$; channel components are continuous and bounded on compact sets, with $S_\cdot \geq 0$, $T_\cdot \geq 0$, and $C_\cdot$ potentially positive or negative depending on sector technology and substitution.

In low capacity, Forward can raise CI if scale dominates and technique has not yet been adopted, whereas Backward can reduce CI if imported equipment/feedstocks directly reconfigure the mix. Above the relevant thresholds, technique and composition dominate and the signs attenuate or reverse: $EI\downarrow$, $CI\downarrow$, $R\uparrow$. Econometrically, the main DPTR estimates a common threshold γ using firm growth as the regime variable, delivering regime-specific coefficients on V_{it} (or on F_{it} and B_{it} in channel-specific equations); robustness tables can probe whether channel-specific thresholds $(g_F^\star, g_B^\star)$ better match the data.

Normalizations, bounds, and units. CES weights are normalized $\sum_s \omega_s = 1$. The efficiency map satisfies $\lambda(G) \in [0, \bar{\lambda})$ with $\bar{\lambda} < 1$; $\lambda(G) = \bar{\lambda}(1 - e^{-\kappa G})$ is an admissible example. Emission factors are reported in tCO_2 per heat unit.

3 Empirical Framework

3.1 Dynamic Panel Threshold Regression

Several studies suggest that energy consumption and carbon emissions are non-linear functions of a country's GVC participation (Jithin & Ashraf, 2023; Shi, Zhao, et al., 2022; Thanh et al., 2022; J. Wang et al., 2019). Mirroring the Environmental Kuznets Curve (EKC) hypothesis, these studies find that energy consumption and carbon emissions tend to increase at lower levels of GVC participation. However, they may decline as participation deepens, likely due to technological upgrading, efficiency gains, and knowledge spillovers. To capture such non-linear dynamics and regime-dependent effects, researchers have increasingly adopted non-linear panel models—such as Panel Threshold Regression (PTR), Dynamic Panel Threshold Regression (DPTR), and Panel Smooth Transition Regression (PSTR)—particularly in contexts where structural breaks or threshold effects are anticipated (Anderl & Caporale, 2023; Cheikh & Louhichi, 2016; Cheikh & Zaied, 2020; Chen et al., 2019; Jithin & Ashraf, 2023; Kiliç, 2016).

The PTR model, originally proposed by Hansen (1999), identifies structural breaks or regime shifts by estimating threshold values that partition the data into distinct regimes with differing slope coefficients. A grid search procedure is employed to determine the appropriate threshold(s), and the model accommodates single or multiple thresholds, allowing the marginal effects of the explanatory variable to change depending on whether the threshold variable lies above or below certain critical levels (Cheikh & Louhichi, 2016). These models offer a flexible framework for analyzing how the effects of GVC participation on energy and environmental outcomes may vary across different levels of integration or exposure.

The present study employs the dynamic panel threshold regression model developed by Seo and Shin (2016), which is particularly well-suited for addressing potential endogeneity in both the explanatory and threshold variables. While the threshold regression model originally proposed by Hansen (1999) is static in nature, Kremer et al. (2013) extended this framework into a dynamic setting by incorporating lagged dependent variables and addressing endogeneity in the explanatory variables. However, a key limitation of Kremer et al. (2013) approach is its inability to effectively manage cases where the threshold variable itself is endogenous (Gharsallah & Trabelsi, 2024). In contrast, Seo and Shin (2016) model directly addresses this issue, making it more appropriate for empirical applications where endogeneity in both the explanatory and threshold variables is a concern (Gharsallah & Trabelsi, 2024).

This approach is grounded in the Generalized Method of Moments (GMM) using first-difference transformations, which helps to eliminate unobserved fixed effects. Additionally, the model includes a bootstrap linearity test to determine the presence of a threshold effect. The significance of the bootstrap p-values provides statistical confirmation of non-linearity in the relationship under investigation. In line with Seo and Shin (2016), the dynamic panel threshold regression model in this study is specified as follows:

$$y_{it} = \mu_{it} + \delta_1 x'_{it} \mathbb{I}\{q_{it} \leq \gamma\} + \delta_2 x'_{it} \mathbb{I}\{q_{it} > \gamma\} + \varepsilon_{it} \tag{17}$$

Where $i = 1, 2, 3, \ldots, N$ and $t = 1, 2, 3, \ldots, T$, where N and T denote the cross-sectional and time dimensions of the panel, respectively. y_{it} is a scalar stochastic variable of interest and x'_{it} denotes the vector of explanatory variables. $\mathbb{I}\{\cdot\}$ is an indicator function that takes the value 0 or 1; q_{it} is the threshold variable and γ is the threshold parameter. δ_1 and δ_2 represent the effects of x_{it} on y_{it} when $q_{it} \leq \gamma$ and $q_{it} > \gamma$, respectively. μ_i captures the country-level fixed effects, and ε_{it} is the random disturbance term, assumed to be independently and identically distributed. The equation (1) can be re-specified as:

$$y_{it} = \begin{cases} \delta_1 x'_{it} + \varepsilon_{it}, & q_{it} \leq \gamma \\ \delta_2 x'_{it} + \varepsilon_{it}, & q_{it} > \gamma \end{cases} \tag{2}$$

As a next step, the fixed effects (μ_{it}) must be eliminated using a fixed-effects transformation. However, the first-differencing or within-transformation approaches cannot be used as they violate the underlying distributional assumption (Hansen, 1999). Instead, a forward orthogonal deviation approach suggested by Arellano and Bover (1995) can be used to eliminate the fixed effects, and it can be specified as follows:

$$\varepsilon_{it}^{*} = \sqrt{\frac{T-t}{T-t+1}} \left[\varepsilon_{it} - \frac{1}{T-t} \left(\varepsilon_{i(t+1)} + \cdots + \varepsilon_{iT} \right) \right] \tag{3}$$

The technique has the advantage of addressing the serial correlation of the transformed error terms. The dynamic panel threshold model offers distinct advantages over conventional linear regression models. First, it addresses the issue of endogeneity by allowing for a non-linear relationship between the variables. Second, this model enables the understanding of complex relationships between the variables by allowing relationships to vary as a function of the threshold variable, an aspect that would not be captured by traditional linear models effectively. Third, it also facilitates the modelling of changes in the relationship between variables differently for different units of the panel. This advantage helps account for heterogeneity across units, such as firms or countries. Lastly, this model facilitates the use of wide range of functional forms, thereby increasing its flexibility to incorporate complex data structures. Despite these advantages, a major limitation of dynamic panel threshold regression is its inability to accommodate multiple thresholds in the regression framework (Jithin & Ashraf, 2023; Seo et al., 2019).

3.2 Data and Measures

The dataset employed in this study is derived from Prowess I.Q., a comprehensive corporate database maintained by the Centre for Monitoring Indian Economy (CMIE). The database offers annual financial and operational data for a broad spectrum of Indian firms and covers the period from 2010 to 2024. For this analysis, the study focuses on firms listed on India's two major stock exchanges—the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE).

Initially, the dataset comprised information from 1,909 firms that reported physical energy consumption data, resulting in a total of 36,231 firm-year observations. However, as the current analysis requires a balanced panel, the final sample was restricted to 143 firms, resulting in 2,145 firm-year observations. The use of listed firms on the NSE and BSE ensures greater consistency and disclosure in reporting, making them well-suited for a firm-level empirical investigation of energy efficiency, carbon emissions, renewable energy consumption, and GVC participation. The detailed data and variable descriptions are provided in Table 1.

3.2.1 Energy Efficiency and Renewable Energy Consumption

In line with existing literature, this study defines energy consumption (or intensity) as an inverse proxy for energy efficiency, following the approach adopted by Cantore et al. (2016), Bagchi et al. (2022), and Pal et al. (2024). Consistent with Pal et al. (2024), this study employs a direct measure of energy consumption, rather than relying exclusively on monetary proxies. Earlier research has frequently used the ratio of power and fuel expenditures to total output as a proxy for energy use. However, such expenditure-based measures are constrained by definitional and computational limitations—particularly due to price volatility and the aggregation of heterogeneous fuel types, which can distort true consumption levels (for a detailed critique, see Pal et al. (2024)).

To address the limitations associated with expenditure-based proxies, this study utilizes energy consumption data reported in physical units as available from the CMIE Prowess database. This methodological choice enables a more accurate and transparent assessment of firm-level energy use. A similar approach is adopted by Bagchi et al. (2022), who also rely on physical units for analyzing energy consumption.

However, as the Prowess database does not adhere to a standardized reporting format for energy units across firms, all reported energy quantities were converted into a common unit using conversion factors specified in the PAT scheme notifications, published in the Official Gazette of the Government of India. For the 143 firms retained in the final balanced panel, approximately 200 distinct energy sources were identified. To ensure consistency in measurement and facilitate comparability, each energy source—whether renewable or non-renewable—was converted into a standard unit, kilocalories (kcal), for analytical purposes. The detailed methodology for unit conversion, along with the complete list of energy sources and their corresponding conversion factors, is presented in Appendices A.1 and A.2. This standardization enables meaningful comparisons of energy

Table 1: Variable Definitions and Summary Statistics

Variables	Definition	Obs.	Mean (SD)
Dependent Variables			
Energy intensity	The ratio of energy consumption (physical unit) to total sales (monetary), Pal et al. (2024).	2145	870529377.6 (25246880736)
Carbon intensity	The ratio of carbon emissions (physical unit) to total sales (monetary), Bagchi et al. (2022)[1].	2145	400464.3 (10699692.76)
Renewable energy consumption	Aggregation of renewable energy sources (physical units measured in kcal), Gozgor et al. (2020).	2145	11070633726 (47955055060)
Independent Variables			
Firm growth	The difference between current total assets and lagged total assets divided by lagged total assets, Titman et al. (2013).	1999[3]	0.0872 (0.2517)
Overall GVC participation	The ratio of imports of raw materials, stores and spares, capital goods and services to expenditure on raw materials, stores and spare, gross fixed assets and services; multiplied by exports-to-sales ratio, Banga (2022).	2145	0.0255 (0.0635)
Forward participation	The ratio of imports of raw materials, stores and spares, capital goods and services to expenditure on raw materials, stores and spare, gross fixed assets and services .	2145	0.2045 (0.3064)
Backward participation	The ratio of exports to total sales.	2145	0.1018 (0.1679)
Labor intensity	The ratio of wages and salaries to employees to total sales, Chauhan and Thangavel (2025)[2]; U. K. Sahu et al. (2024)[1].	2145	0.1221 (1.0303)
Raw material intensity	The ratio of expenditure on raw materials and spares to total sales, Kumar et al. (2023); Chauhan and Thangavel (2025)[2]; U. K. Sahu et al. (2024)[1].	2145	0.5255 (0.2167)
Software intensity	The ratio of sum of IT-enabled services charges, software charges, and other professional services to total sales, U. K. Sahu et al. (2024)[1].	2145	0.0202 (0.4003)
R&D intensity	The ratio of R&D expenditure to total sales, Bagchi et al. (2022)[1]; Pal et al. (2024);Oak and Bansal (2022).	2145	0.0059 (0.0828)
ETI	The ratio of expenditure on imported capital goods to total sales, Bagchi et al. (2022)[1]; Chauhan and Thangavel (2025)[2].	2145	0.0048 (0.0251)
DTI	The ratio of royalties and technical fees in foreign currency to net sales, Bagchi et al. (2022)[1]; Chauhan and Thangavel (2025)[2].	2145	0.0001 (0.0018)

Note: [1]The variables are presented prior to log transformation. [2]Studies use net sales instead of total sales.
[3]Chauhan and Thangavel (2025) calculated technological intensity as embodied plus disembodied.
[4]The difference in the number of observations is due to missing values in the dataset.

consumption across firms and over time.

In addition to measuring energy intensity, this study constructs renewable energy consumption to investigate whether firms' participation in Global Value Chains (GVCs) is associated with a transition towards renewable energy sources. For this purpose, all energy sources reported in the Prowess database were categorized into renewable and non-renewable types, following the classification framework provided by Das and Mahalik (2023). The quantities of renewable energy were then converted into a common unit—kilocalories (kcal)—and aggregated to compute firm-level renewable energy consumption.

3.2.2 Carbon Emissions and Carbon Intensity

Similar to the treatment of energy efficiency, this study employs carbon emissions intensity as an inverse proxy for carbon productivity, consistent with the methodology used by Bagchi et al. (2022). To estimate firm-level carbon emissions, each type of energy source reported in the Prowess database was converted into its corresponding CO_2 emissions using standardized emission factors (measured in kilograms of CO_2 per unit of energy). These emission factors are sourced from the U.S. Environmental Protection Agency (EPA) and align with those used in Barrows and Ollivier (2018, 2021).

The detailed conversion methodology, including the specific emission factors applied to each energy source, is provided in Appendix A.3. This approach enables a consistent and transparent estimation of carbon emissions based on physical energy consumption data, enhancing the robustness of the analysis.

3.2.3 Measuring GVC Participation at the Firm Level

According to Antràs (2020), a GVC is defined as *"a series of stages involved in producing a product or service that is sold to consumers, with each stage adding value, and with at least two stages being produced in different countries. A firm participates in a GVC if it produces at least one stage in a GVC."* A key implication of this definition is that GVC-participating firms are typically engaged in both importing and exporting activities. At the firm level, GVC analysis often treats firms as two-way traders, primarily due to the absence of sufficiently granular micro-level data that would allow for the identification of specific production stages across borders.

To measure overall GVC participation, prior studies have frequently employed a dummy variable approach, assigning a value of 1 if a firm simultaneously imports intermediate goods and exports intermediate or final goods at a given point in time (Ehab & Zaki, 2021; Rigo, 2021; Urata & Baek, 2020). While straightforward, this binary approach fails to capture the intensity or magnitude of a firm's engagement in GVCs.

To overcome this limitation, the present study adopts the Vertical Specialization (VS) index originally proposed by Hummels et al. (2001) at the country level, and later adapted for firm-level analysis by Banga (2022) and Reddy and Sasidharan (2021), to measure the extent of GVC participation. The VS index offers a robust and quantitative measure of a firm's integration into global value chains by capturing the share of imported intermediate inputs that are embodied in exports. In essence, it reflects the foreign value-added content of exports. The vertical specialization index for firm s in year t is computed as:

$$VS_{st} = \frac{\textit{import of; raw materials, stores and spares, capital goods, services}_{st}}{\textit{expenditure on; raw materials, stores and spares, gross fixed assets, services}_{st}} \times \frac{Exports_{st}}{Sales_{st}}$$

Here, $\mathbf{VS}_{st}$ denotes the extent of imported intermediate inputs embodied in firm-level exports, normalized by total material inputs, following the approach of Banga (2022). The numerator of the VS index comprises the total value of imported raw materials, imported stores and spares, imported capital goods, and imports of services. The denominator includes the firm's total expenditure on raw materials, stores and spares, gross fixed assets, and services. The value of $\mathbf{VS}_{st}$ ranges between 0 and 1, where a value of 1 indicates a firm that exclusively relies on foreign inputs and sells its entire output in foreign markets. $\mathbf{VS}_{st}$ is used as a proxy to measure overall GVC participation in the study.

In addition to measuring overall GVC participation, this study further decomposes the VS index into two components: backward and forward participation.

- **Backward participation** reflects the extent to which a firm imports intermediate inputs—such as raw materials, stores and spares, capital goods, and services—for the production of goods that are subsequently exported. This captures the firm's upstream integration into global value chains.

- **Forward participation**, by contrast, refers to the share of a firm's output—intermediate or final goods—that is exported and subsequently used by foreign firms, including other exporters, thereby indicating downstream engagement in GVCs.

$$\text{Backward participation} = \frac{\textit{import of ; raw materials, stores and spares, capital goods, services}_{st}}{\textit{expenditure on; raw materials, stores and spares, gross fixed assets, services}_{st}}$$

$$\text{Forward participation} = \frac{Exports_{st}}{Sales_{st}}$$

Due to the lack of disaggregated information in the Prowess database, it is not possible to distinguish between intermediate and final goods in firms' export data. Consequently, this study employs the ratio of total export earnings to total sales as a proxy for forward participation in global value chains. While this measure does not explicitly capture whether exports are used as intermediate inputs by foreign firms, it serves as a reasonable approximation of a firm's output-side engagement in global markets. Given these data limitations, the proxy reflects the extent to which firms are integrated into the downstream segments of GVCs through their export activities.

4 Estimation Results

This study employs a dynamic panel threshold regression model to examine the nonlinear impact of overall GVC participation and its components—backward and forward participation—on three key firm-level environmental indicators: energy intensity, renewable energy consumption, and carbon intensity. The model incorporates firm growth as the threshold variable, allowing the analysis to identify a critical growth level at which the relationship between GVC participation and the dependent variables undergoes a structural shift. This approach captures potential asymmetries in how GVC integration influences environmental performance across firms with different growth trajectories. By rejecting the null hypothesis of linearity, the supW bootstrap linearity test confirms the presence of nonlinearity in all the models of the study.

4.1 Overall GVC Participation and Firm-Level Environmental Performance

Table 2 presents the results on the impact of overall GVC participation on energy intensity and carbon intensity. The findings reveal that the lagged values of both energy and carbon intensity exert a statistically significant and positive effect on their current levels. This relationship holds for firms in both low-growth and high-growth regimes, indicating that firms tend to maintain a trajectory consistent with their past production patterns. Specifically, firms that exhibited higher energy and carbon consumption per unit of output in the previous year are likely to sustain or even intensify these levels in the current year. This persistence may be attributed to the momentum in production scaling, where firms continue expanding output along the same energy-use path, regardless of their growth status. The results underscore the path-dependent nature of energy and carbon intensity in firms, suggesting limited short-term responsiveness to changes in firm growth alone.

The results further indicate a nonlinear relationship between GVC participation and both energy and carbon intensity, contingent upon the firm's growth regime. Specifically, GVC participation exerts a positive and significant impact on energy and carbon intensity for low-growth firms, whereas it has a negative and significant impact for high-growth firms. In other words, participation in global value chains is associated with increased energy efficiency and enhanced carbon productivity among high-growth firms. Conversely, low-growth firms experience higher energy and carbon intensity, suggesting that the benefits of GVC participation in terms of environmental performance are not uniform across firms, but rather depend on their growth capacity and ability to adapt to the demands of international production networks.

This divergence can be attributed to several structural and operational challenges faced by low-growth firms. As they integrate into GVCs, these firms often encounter barriers such as production disruption risks, capital investment constraints, information asymmetries, limited adjustment time, and a low prioritization of energy efficiency. Financial constraints impede their ability to adopt and upgrade to cleaner and more efficient technologies, thereby restricting innovation. As a result, these firms are often confined to low value-added segments of the GVC, which tend to be energy- and carbon-intensive by nature. Jithin and Ashraf (2023) discuss this "low value-added trap" prevalent in low-growth economies, where firms' limited technological capacity contributes to higher energy intensity and emissions.

In contrast, high-growth firms typically possess the financial and organizational capacity to invest in research and development (R&D) and to absorb transferred technologies, enabling them to reduce their energy and carbon footprints. These firms are more likely to adopt environmentally sustainable practices, often in compliance with international environmental standards and certifications, which are increasingly demanded by lead firms in global production networks. As noted by Wu et al. (2020), such compliance helps minimize the risk of exclusion from GVCs.

Moreover, S. Wang et al. (2021) emphasize the importance of the degree of GVC participation in determining its environmental outcomes. Their study shows that below a critical threshold, increased participation may exacerbate carbon emissions due to technology adoption without corresponding absorptive capacity. However, beyond that threshold, technological advancement can lead to a reduction in emissions, aligning with the observed outcomes for high-growth firms in this study.

These findings highlight that firm-level heterogeneity, especially in terms of growth capacity, plays a critical role in shaping the environmental implications of GVC integration. The results indicate a negative and statistically significant impact of R&D intensity on carbon intensity for high-growth firms, lending further support to the earlier argument that high-growth firms are better positioned to reap environmental benefits from GVC participation. Additionally, we observe a negative but statistically insignificant relationship between R&D intensity and energy intensity for high-growth firms. High-growth firms possess an absolute advantage over low-growth firms in undertaking R&D due to superior access to markets, financial resources, and the benefits of economies of scale and scope. Existing literature supports this view, showing that firms with substantial R&D

investments tend to exhibit lower energy intensity (Golder, 2011; Misra, 2019; Oak & Bansal, 2017; S. Sahu & Narayanan, 2010; Sharma et al., 2019). Improved energy efficiency reduces dependence on fossil fuels by lowering energy requirements in the production process, thereby contributing to reduced carbon emissions.

In contrast, for low-growth firms, R&D intensity has a positive and statistically significant effect on both energy and carbon intensity. This suggests that, for these firms, the costs of adopting energy-efficient technologies may outweigh the short-term benefits, particularly when they face financial constraints and are focused on survival and profitability rather than innovation. As Habtewold (2023) notes, firms with better access to credit and institutional support—including a strong legal framework—are more likely to achieve energy-efficient and carbon-productive outcomes from their R&D investments. Therefore, the efficacy of R&D in promoting sustainable production practices is contingent not only on the level of investment but also on firm-specific characteristics and the enabling environment.

The findings related to R&D intensity are further corroborated by the results on software intensity. For low-growth firms, software intensity has a positive impact on both energy efficiency and carbon productivity, whereas for high-growth firms, the impact is negative. This divergence can be partly explained by the nature of IT-enabled and software services, which often rely on data centers that consume substantial electricity for data processing and server cooling. Without a strong emphasis on sustainability and energy optimization, firms may struggle to manage and reduce the power consumption associated with these operations.

Moreover, the results indicate that both embodied and disembodied technological intensity contribute to improvements in energy efficiency and carbon productivity among high-growth firms. This is consistent with the findings of S. K. Sahu and Narayanan (2012), who show that the importation of new embodied and disembodied technologies and knowledge from abroad facilitates improvements in energy efficiency. Conversely, embodied technological intensity appears to increase energy consumption in low-growth firms, as evidenced by the positive and statistically significant coefficient. This may be due to financial constraints limiting these firms' ability to effectively adopt and integrate new technologies in an energy-efficient manner.

The analysis further reveals that raw material, stores, and spares intensity has a positive impact on both energy and carbon intensity across both low and high growth firms. A plausible explanation is that scaling up production necessitates increased use of these inputs, which in turn drives higher energy consumption and consequently greater carbon emissions. Moreover, if firms invest in low-quality raw materials, stores, and spares, this can significantly impair overall output and reduce energy efficiency (Kumar et al., 2023).

Regarding labor intensity, the results show a positive effect on energy and carbon intensity in low-growth firms, whereas a negative effect is observed for high-growth firms. Given India's labor-intensive economic structure, firms often employ labor to manually operate and manage machinery to address unemployment challenges. The skill level of labor plays a crucial role in determining how efficiently industrial processes utilize energy and control emissions. Employing less skilled labor and experiencing lower labor productivity can hinder efficient energy use, resulting in increased energy and carbon intensity (Kumar et al., 2023; Soni et al., 2017; Subrahmanya, 2006). This dynamic likely explains why increased labor intensity correlates with higher energy consumption among low-growth firms.

In contrast, high-growth firms often use a balanced mix of labor and capital. Studies such as Acs et al. (2008) demonstrate that high-growth firms in the USA exhibit greater labor productivity than their low-growth counterparts. In these firms, proper training and skill development are critical, enabling laborers to better understand the technical operation of machinery, which enhances both energy efficiency and carbon productivity.

The impact of overall GVC participation on renewable energy consumption for both low-growth and high-growth firms is also examined, with the results presented in Table 3. The findings reveal that overall GVC participation has a negative effect on renewable energy consumption for low-growth firms, while exhibiting a positive effect for high-growth firms.

Table 2: Impact of overall GVC participation on energy and carbon intensity – Threshold regression results

Variables	**Energy intensity**		**Carbon intensity**	
	lower regime	**upper regime**	**lower regime**	**upper regime**
Threshold	0.164***	0.164***	0.177***	0.177***
	(0.002)	(0.002)	(0.002)	(0.002)
Lag y	0.476***	0.119***	0.464***	0.104***
	(0.001)	(0.002)	(0.002)	(0.002)
Overall GVC participation	1.862***	-3.184***	0.368***	-2.673***
	(0.128)	(0.122)	(0.067)	(0.096)
Labor intensity	0.077***	-0.868***	0.081***	-1.456***
	(0.002)	(0.115)	(0.002)	(0.088)
Raw material intensity	0.260***	0.384***	0.187***	0.201***
	(0.010)	(0.023)	(0.011)	(0.034)
Software intensity	0.217***	-1.516***	0.208***	-1.167***
	(0.001)	(0.057)	(0.001)	(0.057)
R&D intensity	1.543***	-0.630	1.485***	-17.670***
	(0.007)	(0.509)	(0.004)	(0.919)
ETI	3.830***	-2.443***	0.067	-3.168***
	(0.249)	(0.227)	(0.172)	(0.326)
DTI	-1.383	-259.986***	1.597	-29.405*
	(1.701)	(28.462)	(1.179)	(15.765)
Constant	–	-2.003***	–	-0.787***
		(0.026)		(0.024)
Threshold (F-test)	–	25.44***	–	40.16***
Threshold effect	–	Yes	–	Yes

Note: Firm growth is employed as the transition variable in this study. The dependent variables (energy intensity and carbon intensity) and the key explanatory variable (overall GVC participation) are expressed in logarithms. Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Participation in global value chains facilitates the adoption of new environmental and energy-saving technologies through technology diffusion and labor transfer. These technology spillovers and the exchange of technical knowledge contribute to reducing carbon emissions and promoting a transition towards renewable energy sources (De Marchi et al., 2013, 2018; Javorcik, 2004; Ramanathan et al., 2014). However, this shift from non-renewable to renewable energy is more feasible for high-growth firms, which typically face fewer financial constraints compared to their low-growth counterparts.

For low-growth firms, the transition to renewable or clean energy is often financially prohibitive due to the substantial capital investments required. Moreover, effective extraction and utilization of renewable energy depend critically on adequate infrastructure, grid connectivity, and a trained workforce with relevant technical expertise (Olabi et al., 2023). Furthermore, high-growth firms integrated into GVCs are generally better equipped to manage challenges such as heightened competition and increased production demands. As a result, these firms can simultaneously enhance efficiency in non-renewable energy use while expanding renewable energy consumption to satisfy production requirements.

In line with these observations, the results indicate that investments in R&D positively influence renewable energy consumption, regardless of whether firms are classified as high growth or low growth. Technological breakthroughs driven by R&D investment can reduce the costs associated with renewable energy, thereby fostering greater energy efficiency and supporting a sustainable energy future (Churchill et al., 2021). Additionally, R&D helps overcome technical barriers, such as the lack of expertise required to manage and operate renewable energy systems, as well as infrastructural challenges that impede the integration of renewable energy into the grid (Hayat et al., 2023; Painuly & Wohlgemuth, 2021). The transition to a low-carbon economy necessitates sustained and uninterrupted investment in renewable energy technologies (Zapata et al., 2024). Strengthening R&D efforts is therefore critical to decoupling economic growth from carbon emissions.

Table 3: Impact of overall GVC participation on renewable energy consumption – Threshold regression results

Variables	**Renewable energy consumption**	
	lower regime	**upper regime**
Threshold	0.111***	0.111***
	(0.0001)	(0.0001)
Lag y	0.527***	-0.102***
	(0.0002)	(0.0004)
Overall GVC participation	-3.477***	3.345***
	(0.045)	(0.055)
Labor intensity	-0.019***	13.474***
	(0.001)	(0.053)
Raw material intensity	0.590***	-0.749***
	(0.005)	(0.011)
Software intensity	0.050***	-3.022***
	(0.000)	(0.055)
R&D intensity	0.059***	6.335***
	(0.002)	(0.122)
ETI	3.735***	-5.210***
	(0.099)	(0.122)
DTI	-3.402***	-121.689***
	(0.026)	(1.919)
Constant	–	-0.091***
		(0.007)
Threshold (F-test)	–	82.86***
Threshold effect	–	Yes

Note: Firm growth is employed as the transition variable in this study. The dependent variable (renewable energy consumption) and the key explanatory variable (overall GVC participation) are expressed in logarithms. Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2 Channel-Specific Effects of GVC Participation: Forward vs. Backward

This section presents the results of the disaggregated analysis of GVC participation to determine whether forward and backward participation have distinct impacts on energy intensity, carbon intensity, and renewable energy consumption.

Table 4 shows that forward participation in GVCs has a negative and statistically significant impact on both energy and carbon intensity for high growth firms. On the other hand, forward participation by low growth firms leads to an increase in both energy intensity and carbon intensity. When firms engage in exporting, they tend to adopt new environment friendly technologies and better management practices to reduce energy and carbon intensity (Golder, 2011). Forward participation requires high quality technological learning to meet the foreign market requirements and to promote energy and carbon efficiency (Cai et al., 2020; Qu et al., 2020). The primary determinant for this argument to hold is that whether firms have adequate financial resources to invest in technology, innovation and infrastructure, otherwise export participation may actually lead to increase in energy and carbon intensity. For low growth firms, financial constraints hamper the energy and carbon efficiency gains from technology upgradation linked to participation in GVCs.

The results for backward participation reveal a negative and statistically significant impact on carbon intensity for low-growth firms, whereas the impact is positive for high-growth firms. Backward participation in GVCs typically involves low value-added activities, such as production or manufacturing processes that are highly energy- and carbon-intensive. Moreover, the technological benefits related to energy and production efficiency tend to be limited in backward participation, as the technological standards required are less stringent and less monopolistic (Shi, Shan, et al., 2022). (Qian et al., 2022) show that backward participation leads to an increase in carbon pollution due to trade scale expansion, especially in low-tech industries. Conversely, forward participation helps reduce carbon pollution, primarily in medium- and high-tech industries, driven by advancements in production technology. Shi, Shan, et al. (2022) further conclude that while forward participation reduces carbon emissions in developed countries, backward participation decreases emissions in developed countries but increases them in developing countries.The results show that backward participation can help firms use less energy per output. However, the energy they utilize for their operations tend to be carbon intensive.

Table 4: Impact of forward and backward participation on energy and carbon intensity – Threshold regression results

Variables	**Energy intensity**		**Carbon intensity**	
	lower regime	**upper regime**	**lower regime**	**upper regime**
Threshold	0.149***	0.149***	0.191***	0.191***
	(0.001)	(0.001)	(0.002)	(0.002)
Lag y	0.514***	0.075***	0.444***	0.122***
	(0.002)	(0.002)	(0.003)	(0.003)
Forward participation	0.350***	-1.520***	0.137***	-0.335***
	(0.035)	(0.043)	(0.030)	(0.064)
Backward participation	-0.003	-0.175***	-0.442***	0.428***
	(0.036)	(0.024)	(0.038)	(0.055)
Labor intensity	0.075***	-1.797***	0.074***	-2.196***
	(0.003)	(0.091)	(0.003)	(0.085)
Raw material intensity	0.331***	0.881***	0.364***	0.114***
	(0.012)	(0.029)	(0.011)	(0.029)
Software intensity	0.221***	-0.258**	0.228***	0.216**
	(0.003)	(0.111)	(0.005)	(0.099)
R&D intensity	1.608***	8.903***	1.511***	-8.069***
	(0.016)	(0.968)	(0.009)	(1.182)
ETI	-2.142***	1.141*	6.834***	-8.276***
	(0.493)	(0.595)	(0.454)	(0.615)
DTI	-5.030*	-44.012***	11.310***	112.713***
	(2.946)	(13.880)	(1.341)	(15.961)
Constant	–	-1.374***	–	-1.082***
		(0.028)		(0.026)
Threshold (F-test)	–	24.91***	–	39.10***
Threshold effect	–	Yes	–	Yes

Note: Firm growth is employed as the transition variable in this study. The dependent variables (energy intensity and carbon intensity) and the key explanatory variables (forward and backward GVC participation) are expressed in logarithms. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

In addition, the impact of forward and backward participation on renewable energy consumption is analyzed. For low-growth firms, both forward and backward participation negatively affect renewable energy consumption, whereas for high-growth firms, the impact is positive. These results, presented in Table 5, are consistent with the findings on overall GVC participation and renewable energy consumption. The adoption and development of eco-technologies and renewable energy require enhanced knowledge, learning, and innovation—processes that are facilitated by participation in GVCs (Wu et al., 2020). To fully harness the benefits of GVC participation, firms need adequate infrastructure, skilled human capital, strong institutional support, and effective research and development. High-growth firms are better equipped with professional management, a strong market position, and access to private equity or venture capital, enabling them to improve infrastructure, grid connectivity, and the technical expertise necessary for transitioning from nonrenewable to renewable energy sources. In contrast, low-growth firms often face challenges such as production disruption risks when participating in GVCs, making it difficult to balance production demands with a switch to cleaner energy sources.

Table 5: Impact of forward and backward participation on renewable energy consumption – Threshold regression results

Variables	**Renewable energy consumption**	
	lower regime	**upper regime**
Threshold	0.108***	0.108***
	(0.000)	(0.000)
Lag y	0.518***	-0.096***
	(0.001)	(0.000)
Forward participation	-0.236**	0.519***
	(0.018)	(0.013)
Backward participation	-2.558***	2.311***
	(0.041)	(0.053)
Labor intensity	-0.023***	13.505***
	(0.001)	(0.079)
Raw material intensity	0.716***	-1.064***
	(0.008)	(0.019)
Software intensity	0.056***	-2.239***
	(0.001)	(0.043)
R&D intensity	0.070***	4.054***
	(0.002)	(0.096)
ETI	4.272***	-4.703**
	(0.057)	(0.079)
DTI	-3.333***	-123.984***
	(0.056)	(2.196)
Constant	–	-0.281***
		(0.017)
Threshold (F-test)	–	82.58***
Threshold effect	–	Yes

Note: Firm growth is employed as the transition variable in this study. The dependent variables (renewable energy consumption) and the key explanatory variables (forward and backward GVC participation) are expressed in logarithms. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.3 Robustness Checks

This study conducted two robustness checks to assess the sensitivity of results to alternative empirical models, estimation methods and additional instruments. As a first robustness check, the present study employs the dynamic system Generalized Method of Moments (GMM) estimator developed by Arellano and Bover (1995)) and Blundell and Bond (1998). This method addresses key econometric issues commonly encountered in dynamic panel data models, such as dynamic panel bias and endogeneity. Table 6 presents the estimation results, examining the impact of overall GVC participation on energy intensity, carbon intensity, and renewable energy consumption. The findings indicate that the lagged values of the dependent variables are positive and statistically significant, suggesting strong persistence over time. It shows, firms tend to maintain or intensify their prior levels of energy and carbon intensity, as well as renewable energy use. Furthermore, the results imply that firms tend to be more energy and carbon efficient during the initial stages of growth. However, beyond a certain threshold, these firms engage in more resource-intensive activities to sustain growth. Importantly, the results reveal that, beyond a threshold, overall GVC participation significantly reduces both energy and carbon intensity, while positively influencing renewable energy consumption. These outcomes suggest that firms integrated into global value chains tend to adopt more efficient management practices and environmentally friendly technologies, leading to improved energy efficiency and reduced emissions over time. Additionally, GVC participation promotes learning, innovation, and knowledge transfer, which facilitates the transition to renewable energy sources. These findings are consistent with the baseline dynamic panel threshold regression results, thereby reinforcing the robustness and credibility of the study's conclusions.

Table 6: Regression results from GMM: Energy intensity, Carbon intensity, and Renewable energy consumption

Variables	**Energy intensity**	**Carbon intensity**	**Renewable energy consumption**
Lag y	0.401***	0.418***	0.535***
	(0.002)	(0.002)	(0.000)
Overall GVC participation	20.665***	17.999***	-52.990***
	(0.441)	(0.443)	(0.250)
Overall GVC participation squared	-74.127***	-62.123***	114.728***
	(1.665)	(1.627)	(0.572)
Firm growth	-2.359***	-2.546***	-0.867***
	(0.020)	(0.027)	(0.012)
Firm growth squared	0.380***	0.409***	0.571***
	(0.006)	(0.006)	(0.003)
Constant	8.088***	3.791***	3.410***
	(0.048)	(0.031)	(0.017)
Controls	Yes	Yes	Yes
AR(1) p-value	0.00	0.00	0.00
AR(2) p-value	0.924	0.948	0.934
Hansen p-value	0.149	0.123	0.287

Note: Controls include firm level characteristics (labor intensity, raw material intensity, software intensity, R&D intensity, ETI and DTI). Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

As a second robustness check, this study includes the second lag of the dependent variables as instruments in the dynamic panel threshold regression. This approach accounts for time-dependent patterns in the data and helps address potential endogeneity concerns (Jithin & Ashraf, 2023). The corresponding results are presented in Tables A.3 and A.4. The findings reveal that GVC participation has a positive and significant effect on energy and carbon intensity for low-growth firms, while exerting a negative and significant effect for high-growth firms. Additionally, GVC participation negatively influences renewable energy consumption among low-growth firms but positively affects it among high-growth firms. These results are consistent with the baseline dynamic panel threshold regression findings, thereby strengthening the robustness and validity of the study's conclusions.

5 Conclusion

Leveraging rich firm-level data from India, this study examines the impact of GVC participation on environmental performance, particularly on energy consumption and carbon emissions. Using a dynamic panel threshold regression model, the analysis assesses the effects of overall GVC participation and its components—-forward and backward linkages on energy efficiency, carbon emissions, and renewable energy consumption. This approach provides a nuanced understanding of how trade-related dynamics within GVCs influence environmental outcomes in a nonlinear and heterogeneous manner.

The results reveal a nonlinear relationship between GVC participation and both energy efficiency and carbon emissions, conditioned by the firm's growth regime. Specifically, for low-growth firms, GVC participation is associated with increased energy use and carbon emissions, whereas for high-growth firms, it leads to reductions in both, thereby enhancing energy efficiency and carbon productivity. Several structural and operational constraints impede low-growth firms from fully leveraging the environmental benefits of GVC integration. These include risks of production disruption, limited access to capital, information asymmetries, inadequate adjustment time, and a low prioritization of energy efficiency. Financial constraints, in particular, hinder their ability to invest in and upgrade to cleaner technologies, restricting innovation and confining these firms to low value-added, energy- and carbon-intensive segments of the GVC.

In contrast, high-growth firms are better positioned to adopt environmentally sustainable practices due to their greater financial and organizational capabilities. They are more likely to invest in R&D, absorb advanced technologies, and comply with international environmental standards, often mandated by lead firms in global production networks. For high-growth firms, R&D investments drive innovation, contributing to reduced carbon emissions and improved energy efficiency. Their superior access to markets and financial resources, along with the benefits of economies of scale and scope, confer an absolute advantage over low-growth firms.

The importation of embodied and disembodied technologies from abroad also enhances energy efficiency, particularly in high-growth firms. However, financial limitations may inhibit low-growth firms from effectively adopting and integrating such technologies. The findings further highlight the importance of a balanced mix of labor and capital in achieving environmental performance. In high-growth firms, adequate training and skill development equip workers to operate machinery efficiently, thereby enhancing both energy efficiency and carbon productivity.

Comparatively, the environmental benefits of backward participation in GVCs are less pronounced than those of forward participation. This may be attributed to the lower value-added nature of backward linkages, which tend to be more energy- and carbon-intensive, and the relatively lax technological standards they entail. Nevertheless, both forward and backward participation positively influence renewable energy consumption in high-growth firms. The development and adoption of eco-technologies and renewable energy require enhanced knowledge, innovation, and learning—processes facilitated by GVC engagement. However, realizing these benefits depends on firms' access to infrastructure, skilled human capital, institutional support, and effective R&D.

Overall, the environmental impacts of GVC participation are asymmetrical across firm growth regimes. High-growth firms are better equipped to capture the environmental dividends of GVC integration. Moreover, firms with stronger access to credit and institutional support including robust legal frameworks are more likely to achieve energy-efficient and carbon-productive outcomes from R&D investments. Thus, the efficacy of GVC participation and R&D in advancing sustainable production practices is contingent not only on the level of investment and nature of GVC integration but also on firm-specific characteristics and the broader enabling environment.

The asymmetry of impacts across growth regimes calls for a differentiated policy mix rather than a uniform "green dividend" assumption. For low-growth firms, priority is to relax financial constraints and build absorptive capacity: targeted green credit lines and guarantee schemes for clean capital investment; performance-linked support for R&D, worker training, and energy management; and shared compliance infrastructure at the cluster level (testing and certification facilities, energy audits, and MRV systems) to reduce fixed costs. For high-growth firms, policy should tilt GVC participation toward forward linkages and lower the cost of renewable adoption: export quality infrastructure and standards alignment, expedited access to imported clean equipment, predictable frameworks for renewable procurement (e.g., corporate PPAs) and grid access, and accelerated depreciation for energy-efficient assets. Cross-cutting governance should align trade, industrial, and energy policy by using transparent, performance-based incentives tied to verified reductions in energy and carbon intensity, strengthening disclosure to reduce information frictions, and sequencing interventions in sectors with the highest intensities. The overarching principle is to *shift the capacity margin*—via finance, R&D, and compliance infrastructure—so that a larger set of firms can translate GVC integration into cleaner production.

References

Acs, Z. J., Parsons, W., & Tracy, S. (2008). *High impact firms: Gazelles revisited* (tech. rep.).

Ahmed, M., Shuai, C., & Ahmed, M. (2022). Influencing factors of carbon emissions and their trends in china and india: A machine learning method. *Environmental Science and Pollution Research*, *29*(32), 48424–48437.

Anderl, C., & Caporale, G. M. (2023). Nonlinearities in the exchange rate pass-through: The role of inflation expectations. *International Economics*, *173*, 86–101.

Antràs, P. (2020). Conceptual aspects of global value chains. *The World Bank Economic Review*, *34*(3), 551–574.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29–51.

Bagchi, P., Sahu, S. K., Kumar, A., & Tan, K. H. (2022). Analysis of carbon productivity for firms in the manufacturing sector of india. *Technological Forecasting and Social Change*, *178*, 121606.

Balachandra, P., Ravindranath, D., & Ravindranath, N. H. (2010). Energy efficiency in india: Assessing the policy regimes and their impacts. *Energy Policy*, *38*(11), 6428–6438.

Banga, K. (2022). Impact of global value chains on total factor productivity: The case of indian manufacturing. *Review of Development Economics*, *26*(2), 704–735.

Barrows, G., & Ollivier, H. (2018). Cleaner firms or cleaner products? how product mix shapes emission intensity from manufacturing. *Journal of Environmental Economics and Management*, *88*, 134–158.

Barrows, G., & Ollivier, H. (2021). Foreign demand, developing country exports, and co2 emissions: Firm-level evidence from india. *Journal of Development Economics*, *149*, 102587.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115–143.

Cai, L., Zhang, Z., & Zhu, L. (2020). Global value chain embeddedness and carbon dioxide emissions—an empirical study based on panel data of china's industries. *J. Int. Trade*, *4*, 86–104.

Cantore, N., Calı, M., & te Velde, D. W. (2016). Does energy efficiency improve technological change and economic growth in developing countries? *Energy Policy*, *92*, 279–285.

Chauhan, A., & Thangavel, M. (2025). Assessing the impact of the perform, achieve, and trade scheme on energy efficiency in india's iron and steel sector. *Energy Policy*, *198*, 114480.

Cheikh, N. B., & Louhichi, W. (2016). Revisiting the role of inflation environment in exchange rate pass-through: A panel threshold approach. *Economic Modelling*, *52*, 233–238.

Cheikh, N. B., & Zaied, Y. B. (2020). Revisiting the pass-through of exchange rate in the transition economies: New evidence from new eu member states. *Journal of International Money and Finance*, *100*, 102093.

Chen, X., Chen, Y. E., & Chang, C.-P. (2019). The effects of environmental regulation and industrial structure on carbon dioxide emission: A non-linear investigation. *Environmental science and pollution research*, *26*(29), 30252–30267.

Churchill, S. A., Inekwe, J., & Ivanovski, K. (2021). R&d expenditure and energy consumption in oecd nations. *Energy economics*, *100*, 105376.

Das, K. C., & Mahalik, M. K. (2023). Renewable energy use and export performance of manufacturing firms: Panel evidence from six industries in india. *Energy Economics*, *125*, 106894.

De Marchi, V., Di Maria, E., & Ponte, S. (2013). The greening of global value chains: Insights from the furniture industry. *Competition & change*, *17*(4), 299–318.

De Marchi, V., Giuliani, E., & Rabellotti, R. (2018). Do global value chains offer developing countries learning and innovation opportunities? *The European Journal of Development Research*, *30*(3), 389–407.

Ehab, M., & Zaki, C. R. (2021). Global value chains and service liberalization: Do they matter for skill-upgrading? *Applied Economics*, *53*(12), 1342–1360.

Gharsallah, M., & Trabelsi, S. (2024). The effect of human capital on the trade-growth nexus: A dynamic panel threshold analysis. *Research in Economics*, *78*(4), 100988.

Golder, B. (2011). Energy intensity of indian manufacturing firms: Effect of energy prices, technology and firm characteristics. *Science, Technology and Society*, *16*(3), 351–372.

Gozgor, G., Mahalik, M. K., Demir, E., & Padhan, H. (2020). The impact of economic globalization on renewable energy in the oecd countries. *Energy Policy*, *139*, 111365.

Habtewold, T. M. (2023). Impacts of internal r&d on firms' performance and energy consumption: Evidence from ethiopian firms. *International Journal of Innovation Studies*, *7*(1), 47–67.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of econometrics*, *93*(2), 345–368.

Hayat, S., Safi, A., Wahab, S., Shahzad, K., & Chen, Y. (2023). Renewable energy r&d and natural resources: A success story of environmentally friendly financing in oecd economies. *Resources Policy*, *83*, 103655.

Huang, Q., Zheng, H., Li, J., Meng, J., Liu, Y., Wang, Z., Zhang, N., Li, Y., & Guan, D. (2021). Heterogeneity of consumption-based carbon emissions and driving forces in indian states. *Advances in Applied Energy*, *4*, 100039.

Hummels, D., Ishii, J., & Yi, K.-M. (2001). The nature and growth of vertical specialization in world trade. *Journal of international Economics*, *54*(1), 75–96.

Humphrey, J., & Schmitz, H. (2002). How does insertion in global value chains affect upgrading in industrial clusters? *Regional studies*, *36*(9), 1017–1027.

Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic firms? in search of spillovers through backward linkages. *American economic review*, *94*(3), 605–627.

Jithin, P., & Ashraf, S. (2023). Global value chain participation and co2 emissions: Does economic growth matter? new evidence from dynamic panel threshold regression. *Energy Economics*, *128*, 107154.

Kiliç, R. (2016). Regime-dependent exchange-rate pass-through to import prices. *International Review of Economics & Finance*, *41*, 295–308.

Kremer, S., Bick, A., & Nautz, D. (2013). Inflation and growth: New evidence from a dynamic panel threshold analysis. *Empirical Economics*, *44*(2), 861–878.

Kumar, A., Mittal, A., & Pradhan, A. K. (2023). Magnitude and determinants of energy intensity: Evidence from indian firms. *Environmental Science and Pollution Research*, *30*(2), 3270–3281.

Lee, C.-C., & Wen, H. (2025). Global value chain embedding and enterprise energy efficiency: A worldwide firm-level analysis. *Renewable and Sustainable Energy Reviews*, *207*, 114955.

Liu, C., & Zhao, G. (2021). Can global value chain participation affect embodied carbon emission intensity? *Journal of Cleaner Production*, *287*, 125069.

Meng, J., Mi, Z., Guan, D., Li, J., Tao, S., Li, Y., Feng, K., Liu, J., Liu, Z., Wang, X., et al. (2018). The rise of south–south trade and its effect on global co2 emissions. *Nature communications*, *9*(1), 1871.

Methmini, D., Dharmapriya, N., Gunawardena, V., Edirisinghe, S., Jayathilaka, R., & Wickramaarachchi, C. (2025). Impact of economic growth, energy consumption, and trade openness on carbon emissions: Evidence from the top 20 emitting nations. *Climate and Development*, *17*(5), 395–406.

Misra, K. (2019). *Impact of perform-achieve-trade policy on the energy intensity of cement and iron and steel industries in india*. Institute for Social; Economic Change.

Oak, H., & Bansal, S. (2017). *Perform-achieve-trade policy: A case study of cement industry for energy efficiency* (tech. rep.). Centre for International Trade and Development, Jawaharlal Nehru University ...

Oak, H., & Bansal, S. (2022). Enhancing energy efficiency of indian industries: Effectiveness of pat scheme. *Energy Economics*, *113*, 106220.

Olabi, A., Elsaid, K., Obaideen, K., Abdelkareem, M. A., Rezk, H., Wilberforce, T., Maghrabie, H. M., & Sayed, E. T. (2023). Renewable energy systems: Comparisons, challenges and barriers, sustainability indicators, and the contribution to un sustainable development goals. *International Journal of Thermofluids*, *20*, 100498.

Painuly, J. P., & Wohlgemuth, N. (2021). Renewable energy technologies: Barriers and policy implications. In *Renewable-energy-driven future* (pp. 539–562). Elsevier.

Pal, K., Mukhopadhyay, J. P., & Bhagawan, P. (2024). Does cap-and-trade scheme impact energy efficiency and firm value? empirical evidence from india. *Energy Economics*, *134*, 107581.

Pietrobelli, C., & Rabellotti, R. (2011). Global value chains meet innovation systems: Are there learning opportunities for developing countries? *World development*, *39*(7), 1261–1269.

Qian, Z., Zhao, Y., Shi, Q., Zheng, L., Wang, S., & Zhu, J. (2022). Global value chains participation and co2 emissions in rcep countries. *Journal of Cleaner Production*, *332*, 130070.

Qu, C., Shao, J., & Cheng, Z. (2020). Can embedding in global value chain drive green growth in china's manufacturing industry? *Journal of Cleaner Production*, *268*, 121962.

Ramanathan, U., Bentley, Y., & Pang, G. (2014). The role of collaboration in the uk green supply chains: An exploratory study of the perspectives of suppliers, logistics and retailers. *Journal of cleaner production*, *70*, 231–241.

Reddy, K., & Sasidharan, S. (2021). Financial constraints and global value chain participation: Firm-level evidence from india. *The Journal of International Trade & Economic Development*, *30*(5), 739–765.

Rigo, D. (2021). Global value chains and technology transfer: New evidence from developing countries. *Review of World Economics*, *157*(2), 271–294.

Roy, J., & Yasar, M. (2015). Energy efficiency and exporting: Evidence from firm-level data. *Energy Economics*, *52*, 127–135.

Sahu, S., & Narayanan, K. (2010). Determinants of energy intensity in indian manufacturing industries: A firm level analysis.

Sahu, S. K., & Narayanan, K. (2012). Labour and energy intensity: A study of the pulp and paper industries in india. In *Human capital and development: The indian experience* (pp. 55–76). Springer.

Sahu, U. K., Kumar, A., & Pradhan, A. K. (2024). Analyzing energy intensity of indian chemical industry: A panel data approach. *Energy Nexus*, *13*, 100279.

Seo, M. H., Kim, S., & Kim, Y.-J. (2019). Estimation of dynamic panel threshold model using stata. *The Stata Journal*, *19*(3), 685–697.

Seo, M. H., & Shin, Y. (2016). Dynamic panels with threshold effect and endogeneity. *Journal of econometrics*, *195*(2), 169–186.

Sharma, A., Roy, H., & Dalei, N. N. (2019). Estimation of energy intensity in indian iron and steel sector: A panel data analysis. *Statistics in Transition new series*, *20*(2), 107–121.

Shi, Q., Shan, Y., Zhong, C., Cao, Y., & Xue, R. (2022). How would gvcs participation affect carbon intensity in the "belt and road initiative" countries? *Energy Economics*, *111*, 106075.

Shi, Q., Zhao, Y., Qian, Z., Zheng, L., & Wang, S. (2022). Global value chains participation and carbon emissions: Evidence from belt and road countries. *Applied Energy*, *310*, 118505.

Soni, A., Mittal, A., & Kapshe, M. (2017). Energy intensity analysis of indian manufacturing industries. *Resource-Efficient Technologies*, *3*(3), 353–357.

Subrahmanya, M. B. (2006). Labour productivity, energy intensity and economic performance in small enterprises: A study of brick enterprises cluster in india. *Energy conversion and management*, *47*(6), 763–777.

Thanh, T. T., et al. (2022). Global value chains and energy security: Evidence from global sample. *Energy Strategy Reviews*, *42*, 100870.

Titman, S., Wei, K. J., & Xie, F. (2013). Market development and the asset growth effect: International evidence. *Journal of Financial and Quantitative Analysis*, *48*(5), 1405–1432.

Urata, S., & Baek, Y. (2020). *The determinants of participation in global value chains: A cross-country, firm-level analysis* (tech. rep.). ADBI Working Paper Series.

Wang, J., Wan, G., & Wang, C. (2019). Participation in gvcs and co2 emissions. *Energy Economics*, *84*, 104561.

Wang, S., He, Y., & Song, M. (2021). Global value chains, technological progress, and environmental pollution: Inequality towards developing countries. *Journal of Environmental Management*, *277*, 110999.

Wang, S., Wang, X., & Chen, S. (2022). Global value chains and carbon emission reduction in developing countries: Does industrial upgrading matter? *Environmental Impact Assessment Review*, *97*, 106895.

World Bank. (2020). Global economic prospects, june 2020.

Wu, Z., Hou, G., & Xin, B. (2020). The causality between participation in gvcs, renewable energy consumption and co2 emissions. sustainability (switzerland), 12 (3).

Yan, Y., Wang, R., Zheng, X., & Zhao, Z. (2020). Carbon endowment and trade-embodied carbon emissions in global value chains: Evidence from china. *Applied Energy*, *277*, 115592.

Zapata, S., Uriona-Maldonado, M., & Herrera, M. M. (2024). The role of renewable energy policy and r&d in renewables diffusion. *Electricity*, *5*(3), 526–545.

Zhang, D., Wang, H., Löschel, A., & Zhou, P. (2021). The changing role of global value chains in co2 emission intensity in 2000–2014. *Energy Economics*, *93*, 105053.

Zheng, L., Zhao, Y., Shi, Q., Qian, Z., Wang, S., & Zhu, J. (2022). Global value chains participation and carbon emissions embodied in exports of china: Perspective of firm heterogeneity. *Science of the Total Environment*, *813*, 152587.

A Appendix

A.1 Calorific conversion methodology for energy intensity

The formula utilized for converting each energy unit into a standard conversion unit (kcal) is as follows:

$$\textbf{Energy (kcal)} = \textbf{Energy (original unit)} \times \textbf{Conversion factor} \tag{1}$$

For example, coal is originally measured in tonnes. The conversion of coal's original unit to kilocalories (kcal) is calculated as follows:

$$\begin{aligned}
\text{Energy from Coal (kcal)} &= \text{Energy (tonnes)} \times \text{Conversion factor (kcal/kg)} \\
&= 1000 \times 3900 \\
&= 3,900,000 \\
&= 39 \times 10^5 \text{ kcal}
\end{aligned}$$

A.2 Energy sources (Renewable and Non- renewable) and their conversion factors

Renewable energy sources: Agro-waste, bagasse, bhoosi, biomass, electricity (wind energy-based, solar energy-based, husk, bagasse), fire-wood, paddy/rice husk, naphtha, nitrogen, oxygen.

Non-renewable energy sources: Coal, coal briquettes, charcoal, coke, diesel, electricity (from coal, furnace oil, natural gas) , electricity through diesel generator ,furnace oil, lignite, liquefied natural gas (LNG), liquefied petroleum gas (LPG), lubricants, natural gas, fuel oils (LDO, HSD, , LSHS), kerosene, non-coking coal , petrol, petroleum coke, propane, steam coal, and other energy sources that do not fall under renewable energy.

Table A.1: *Conversion rates of energy sources*

Solid fuels of energy	**Conversion rates (kcal/kg)**
Coal	2800–5000
Lignite	2500–3000
Pet coke	7500–8500
Rice husk	3200
Bagasse	1900–2100
Wood	3400
Liquid fuels of energy	**Conversion rates (kcal/kg)**
Furnace oil	10000–10500
Diesel	10000
Kerosene	11100
LDO	10700
LSHS	10600
LPG	11600–12500
Naphtha	10050
HSD	11840
Petrol	11200
Gaseous fuels of energy	**Conversion rates (kcal/kg)**
Natural gas	12500
Propane-butane	11950
Electricity	**Conversion rate (kcal/kWh)**
Grid electricity	860

Note: Prowess does not employ the same naming pattern as listed above. So, we manually mapped the names of the energy source given above to the corresponding names given in Prowess.
Source: *PAT (Perform, Achieve, and Trade) scheme notifications published in the official Gazette of the Government of India* and https://cngeurope.com/fuel-calorific-values/

A.3 Conversion methodology and conversion factors for carbon intensity

Similar to the conversion methodology for energy intensity, where we have used conversion factors for each energy source, we have used emission factors for carbon dioxide in this context. The methodology is as follows:

$$\textbf{Emissions from energy source (kg CO}_{\mathbf{2}}\textbf{)} = \textbf{Energy (original unit)} \times \textbf{Emission factor} \tag{2}$$

For example: Agricultural byproducts are originally measured in tonnes. To estimate the emissions produced from using agricultural byproduct as an energy source, the following method is followed:

$$\begin{aligned}\textbf{Emissions (Kg CO}_{\mathbf{2}}\textbf{)} &= \textbf{Energy (tonnes)} \times \textbf{Emission factor (Kg CO}_{\mathbf{2}}\textbf{/short ton)} \\ &= \mathbf{1.10231 \times 975} \\ &= \textbf{1074.75 Kg CO}_{\mathbf{2}}\end{aligned}$$

Table A.2: *Emission Factors for Carbon Dioxide*

Name of the energy	Original unit of energy	Kg CO_2 per unit of energy	Kg CO_2 per MMBTU of energy
Anthracite	short ton	2602	103.69
Agricultural byproducts	short ton	975	118.17
Bagasse	–	–	95.5
Biogas	scf	0.0438	52.07
Bituminous	short ton	2325	93.28
Butane	gallon	6.67	64.77
Coal Coke	short ton	2819	113.67
Coke oven gas	scf	0.02806	46.85
Distillate Fuel Oil No. 1	gallon	10.18	73.25
Distillate Fuel Oil No. 2	gallon	10.21	73.91
Electricity	–	–	278
Fuel gas	scf	0.08189	59
Kerosene	gallon	10.15	75.20
Lignite	short ton	1389	97.72
Liquefied petroleum gas (LPG)	gallon	5.68	65.71
Lubricants	gallon	10.69	74.27
Motor gasoline	gallon	8.78	70.22
Municipal solid waste	short ton	902	90.70
Naphtha (<401 deg F)	gallon	8.50	68.02
Natural gas	scf	0.05444	53.06
Natural Gasoline	gallon	7.36	66.88
Petroleum coke (solid)	short ton	3072	102.41
Propane (Liquid)	gallon	5.72	62.87
Propane gas	scf	0.15463	61.46
Residual Fuel Oil No. 6	gallon	11.27	75.10
Wood and wood residuals	short ton	1640	93.80

Note: Prowess does not employ the same naming pattern as listed above. So, we manually mapped the names of the energy source given above to the corresponding names given in Prowess.
Source: U.S. Environmental Protection Agency (EPA)
https://www.epa.gov/system/files/documents/2025-01/ghg-emission-factors-hub-2025.pdf

A.4 Robustness checks: Additional instruments

Table A.3: Impact of overall GVC participation on energy and carbon intensity – Threshold regression results (Additional instrument)

Variables	**Energy intensity**		**Carbon intensity**	
	lower regime	**upper regime**	**lower regime**	**upper regime**
Threshold	0.164***	0.164***	0.177***	0.177***
	(0.002)	(0.002)	(0.002)	(0.002)
Lag y	0.476***	0.119***	0.464***	0.104***
	(0.001)	(0.002)	(0.002)	(0.002)
Overall GVC participation	1.862***	-3.184***	0.368***	-2.673***
	(0.128)	(0.122)	(0.067)	(0.096)
Constant	–	-2.003***	–	-0.787***
		(0.026)		(0.024)
Controls	Yes	Yes	Yes	Yes

Note: Firm growth is employed as the transition variable in this study. Controls include firm level characteristics (labor intensity, raw material intensity, software intensity, R&D intensity, ETI and DTI). Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Impact of overall GVC participation on renewable energy consumption – Threshold regression results (Additional instrument)

Variables	**Renewable energy consumption**	
	Lower regime	**Upper regime**
Threshold	0.111***	0.111***
	(0.000)	(0.000)
Lag y	0.527***	-0.102***
	(0.000)	(0.000)
Overall GVC participation	-3.477***	3.345***
	(0.045)	(0.055)
Constant	–	-0.091***
		(0.007)
Controls	Yes	Yes

Note: Firm growth is employed as the transition variable in this study. Controls include firm level characteristics (labor intensity, raw material intensity, software intensity, R&D intensity, ETI and DTI). Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.