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Beyond identification: ranking stable CO_2 emission drivers in Malaysia via ML-Enhanced SDA for SDG 13

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Abstract
This study advances understanding of CO_2 emission dynamics in Malaysia by integrating Structural Decomposition Analysis (SDA) with Machine Learning (ML) techniques to identify key emission drivers and evaluate their stability and predictability during 2010-2020. Using multi-year input-output tables and emissions data, an additive SDA framework decomposes changes in CO_2 emissions into six effects: CO_2 intensity, technology (production structure), household expenditure, investment, government expenditure, and exports. Four ML methods, namely Neural Networks with SHapley Additive exPlanations (SHAP), Lasso Regression, Elastic Net Regression, and Bayesian Regression, are applied to rank driver importance at aggregate and sectoral levels. Results show consistent findings across methods, with CO_2 intensity emerging as the most influential and variable driver, followed by technology and household consumption. In contrast, government expenditure, investment, and exports contribute relatively little to emission changes. Sectoral analysis indicates that emissions fluctuations are primarily driven by electricity, gas and water supply, manufacturing, wholesale and retail trade, and transportation. SHAP results further confirm the significance of intensity improvements in the early decade, demand-driven growth in the middle years, and pandemic-related declines in 2019-2020. The findings provide evidence-based insights for climate policy, highlighting the importance of renewable energy adoption, technological upgrading, carbon taxation, and sustainable consumption in supporting Malaysia's net-zero ambitions and Sustainable Development Goal 13.

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1. Introduction

Climate change is increasingly recognized not only as an environmental challenge but also as a business and socioeconomic issue that affects investment decisions, industrial competitiveness, consumer behavior, public policy, and long-term development trajectories. For emerging economies such as Malaysia, balancing economic growth with environmental sustainability has become a strategic priority, particularly as governments and businesses face growing pressure to meet decarbonization commitments while sustaining productivity and employment. In this context, understanding the factors that drive carbon dioxide (CO_2) emissions is essential for designing evidence-based policies, supporting corporate sustainability strategies, and ensuring an equitable transition toward a low-carbon economy.

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Input-output (I-O) analysis has become a cornerstone of energy and emissions research, with structural decomposition analysis (SDA) emerging as a particularly powerful tool for identifying the drivers of changes in CO_2 emissions over time (Su & Ang, 2012, 2017; Wang & Yang, 2023). SDA's strength lies in its ability to capture both production- and demand-side dynamics through inter-industry linkages, making it highly relevant to business and policy analysis by revealing how production decisions, supply chain structures, household consumption patterns, investment activities, and international trade collectively shape environmental outcomes. Therefore, SDA is particularly suited to emerging economies undergoing rapid structural transformations.

Decomposition analyses generally fall into two interrelated categories: index decomposition analysis (IDA), which focuses on the relationship between impacts (e.g. energy use, emissions, or employment) and production levels, and structural decomposition analysis (SDA), which examines linkages with consumption activities. SDA offers greater comprehensiveness than IDA by explicitly capturing production-consumption interdependencies, albeit at the cost of requiring more extensive data. Anchored in I-O frameworks, SDA quantifies the drivers of changes in CO_2 emissions over time, incorporating intersectoral linkages, technological shifts, and demand-side effects often overlooked by IDA (Su & Ang, 2012).

This study is motivated by the alignment of SDA with SDG 13 (Climate Action), which calls for context-specific mitigation strategies in developing nations (United Nations, 2015; IPCC, 2023). Malaysia, an upper-middle-income ASEAN economy that is heavily reliant on fossil fuels, experienced moderate but persistent CO_2 growth from 2010 to 2020, driven by energy demand, industrial processes, and transport (Sandu et al., 2019). Despite per-capita emissions being well below developed-country averages, the pressure to decouple economic growth from emissions remains urgent. From a business and social science perspective, identifying the drivers of emissions is particularly important because climate policies increasingly influence production costs, investment allocation, supply chain decisions, consumer behavior, and social welfare outcomes. Understanding which factors consistently drive emissions can help policymakers prioritize interventions and enable businesses to anticipate transition risks and identify opportunities associated with green growth policies. Therefore, identifying stable, sector-specific drivers is therefore critical for designing targeted policies, including renewable energy transitions under the National Energy Transition Roadmap (NETR), carbon pricing mechanisms introduced in 2026, and demand-side interventions that support Malaysia's net-zero ambitions and advance SDG 13.

With multi-year input-output tables and emissions data available for Malaysia from 2010 to 2020, structural decomposition analysis (SDA) is ideally suited to identify the primary drivers of CO_2 emissions and their stability over time, which is critical for designing robust, evidence-based policies that advance SDG 13 (Climate Action) and Malaysia's net-zero ambitions under the National Energy Transition Roadmap (NETR) and the carbon pricing framework to be introduced in 2026. Traditional SDA applications typically emphasize three production-based drivers: the CO_2 intensity effect, economic structure (technology) effect, and activity or value-added effect. However, extending the framework to incorporate final demand components enables a more comprehensive consumption-based perspective, allowing for the examination of demand-side factors, such as household consumption, investment, government spending, and exports, which are particularly influential in rapidly growing emerging economies (Roman-Collado et al., 2018). From a business perspective, these demand-side components directly reflect market behavior, investment patterns, public expenditure priorities, and trade competitiveness, making their assessment valuable for policymakers and industry stakeholders. This holistic approach is essential for uncovering predictable levers that can guide targeted interventions, from renewable energy transitions and efficiency gains to sustainable consumption patterns, thereby supporting equitable and effective climate mitigation in Malaysia and other ASEAN countries.

The choice of decomposition method is critical. Numerous studies have advanced SDA methodologies based on data characteristics and the desired properties. For newcomers to structural decomposition analysis (SDA), foundational guidance is available in De Boer and Rodrigues (2020), which provides a comprehensive review linking SDA to index number theory and includes a decision tree for selecting methods based on properties such as time-reversal and factor-reversal. This foundational work has inspired numerous innovative applications and refinements. For instance, Su and Ang (2015) proposed four distinct input-output frameworks for aggregate carbon intensity and demonstrated multiplicative SDA on China's trajectory from 2007 to 2010. Building directly on that, Su and Ang (2017) shifted attention to the demand side by developing the aggregate embodied intensity (AEI) concept and applying a multiplicative decomposition. Wang et al. (2017) took multiplicative approaches further, clarifying sub-aggregate breakdowns and bridging them to additive forms and index decomposition analysis (IDA).

A predominant methodology in recent studies on carbon emissions and trade-related environmental impacts is the use of environmentally extended input-output (IO) models, often combined with structural decomposition analysis (SDA) to identify the drivers of changes in emissions. Multi-regional input-output (MRIO) frameworks are frequently employed to trace embodied emissions across global and regional supply chains. For instance, several studies have utilized MRIO models to quantify the emissions embodied in trade and decompose changes into factors such as carbon intensity, production structure, and demand effects (Chen et al., 2025; Nagashima et al., 2025; Yang et al., 2025; Yuan et al., 2024; Zhu et al., 2024; Xu et al., 2024; Sun et al., 2024). SDA is commonly applied to disentangle contributions from technique, composition, and scale effects, with extensions that distinguish domestic and foreign influences or geographic shifts in trade partners (Cotterlaz & Gouel, 2026; Chen et al., 2025; Shimotsuura, 2025). Variations include semi-closed IO models that incorporate household feedback loops (Su & Ang, 2025) and comparisons between open and semi-closed approaches for embodiment analysis. Some studies have integrated SDA with structural path analysis (SPA) to map key emission transmission pathways and identify drivers. This approach is used to reveal sectoral interdependencies and indirect emission flows (Ma et al., 2025; Zhang et al., 2025). Extensions to standard IO models include environmentally extended MRIOs for global supply chain perspectives (Huang et al., 2025; Tausch & Althouse, 2025) and models that distinguish firm-size heterogeneity or technical differences between trading partners (Zhang et al., 2024; Zhao et al., 2025). Other variants incorporate atmospheric circulation data into the SDA to model pollutant transfers (Dall'Erba et al., 2024) or focus on life cycle assessments using IO frameworks (Shimotsuura, 2025). A smaller set employs alternative decompositions, such as labor productivity growth decomposition combined with SDA for structural transformation (Sahel & El Abbassi, 2025) or extended SDA for vertical specialization in production networks (Jiang & Kim, 2024). Subsystem approaches within IO frameworks analyze vertically integrated sectors and employment drivers (Di Berardino et al., 2024). These methodologies predominantly rely on IO databases (e.g. WIOD, GTAP, and ADB MRIO) to capture intersectoral and interregional linkages, highlighting the role of trade in emission transfers and the need for consumption-based accounting.

The literature reveals three critical gaps addressed in this study. First, existing SDA studies predominantly identify emission drivers without assessing whether these rankings are stable or reproducible over time, which is a key requirement for robust policy design. Second, although ML methods have been applied to energy forecasting, their integration with SDA for feature stability analysis remains rare, leaving a methodological void. Third, Malaysia-specific ML-SDA research is absent from the literature, despite the country's strategic importance as a rapidly industrializing ASEAN economy. Addressing these gaps has implications that extend beyond methodological advancements. Stable identification of emission drivers can improve strategic planning by governments, firms, investors, and other stakeholders who must make long-term decisions in the face of increasing climate-related uncertainty. In particular, understanding whether certain drivers consistently influence emissions can enhance confidence in policy priorities, investment strategies, corporate sustainability initiatives, and resource-allocation decisions. Hence, the primary novelty of this study lies in extending SDA beyond driver identification to assess their stability and predictability using machine learning (ML) techniques, a combination that has seen limited application in emission SDA research. This approach is rationalized by its potential to inform robust policies. For instance, stable demand-side drivers could guide Malaysia's macro strategies under the Paris Agreement, potentially reducing emissions through targeted interventions.

For this purpose, we utilize four machine learning (ML) methods to rank Malaysia's emission drivers at the aggregate and sectoral levels, subject to the stability and predictability of this ranking: Neural Networks with Shapley Additive exPlanations (SHAP), Lasso Regression, Elastic Net Regression, and Bayesian Regression. A feed-forward neural network is trained on SDA features, with global importance measured via SHAP for consistent, additive attributions (Lundberg & Lee, 2017); Lasso Regression employs standardized coefficients for importance, prioritizing sparsity (Tibshirani, 1996); Elastic Net provides a balanced perspective on correlated features through standardized coefficients (Zou & Hastie, 2005); Bayesian Regression derives importance from posterior means, incorporating uncertainty (Gelman et al., 2013). We further assessed the predictability of feature importance across bootstrap iterations to bolster confidence in the reproducibility of the results.

This study addresses two central questions: (i) What are the primary CO_2 emission drivers in Malaysia from an input-output perspective, including both production-based (e.g. intensity, structure, and activity) and demand-side factors (e.g. private consumption and exports)? (ii) Which of these drivers exhibited the highest stability and predictability at the aggregate and sectoral levels over the 2010-2020 period? To achieve this, the study's objectives are as follows: (i) to decompose CO_2 emissions using an additive SDA informed by Shapley principles, incorporating both intermediate and final demand; and (ii) to rank driver importance for stability and predictability via four ML methods (Neural Networks with SHAP, Lasso Regression, Elastic Net Regression, and Bayesian Regression). The analysis is scoped to Malaysia's economy-wide data from to 2010-2020, excluding sub-national or international trade extensions to focus on national-level insights.

The significance of this research extends beyond environmental accounting to broader business and social science concerns involving sustainable development, industrial transformation, governance, behavioral change, and economic resilience. By identifying stable and predictable emission drivers, this study provides actionable evidence for corporate sustainability planning, green investment decision-making, sectoral competitiveness assessments, public policy design, and stakeholder engagement strategies. These insights are particularly valuable for developing economies seeking to balance their economic growth, social welfare, and environmental responsibility. Broader impacts include academic contributions to ML-SDA hybrids, potentially influencing global studies and policy recommendations for trade and consumption reforms that could mitigate emissions in similar developing contexts. Collectively, these contributions align with SDG 13 (Climate Action) and provide tools for evidence-based planning. The remainder of this paper is organized as follows. Section 2 details the additive decomposition methodology (informed by Shapley principles) for examining changes in carbon emission intensity and outlines the four ML approaches for driver ranking. Section 3 describes the data sources and presents empirical results for Malaysia. Section 4 concludes with key findings, implications, and policy recommendations.

2. Methodology

2.1 Shapley/Sun additive decomposition analysis

As noted, SDA is a widely used technique in energy and environmental studies for disaggregating observed changes in aggregate indicators, such as CO_2 emissions, into the contributions of underlying drivers, including technology, final demand, and intensity effects. Within the input-output framework, SDA quantifies how changes in economic structure and behavior drive variations in environmental indicators over time, capturing both direct and indirect effects through inter-industry production linkages. Therefore, SDA has been extensively applied in conjunction with input–output models to analyze carbon emissions and their driving forces. However, conventional decomposition methods, such as the Laspeyres, Paasche, and Divisia indices, are often subject to path dependence and may produce residual terms that represent unexplained portions of the total change when multiple factors are considered. To address these limitations, the Shapley value approach derived from cooperative game theory offers a path-independent and exact decomposition, ensuring zero residuals and fair attribution of effects across factors (Liang et al., 2018).

2.1.1 Input–Output accounting for CO_2 emissions

In the Environmental I-O model following Ueda (2022), total CO_2 emissions in period $t \in \{0,1\}$ are expressed as:

$$C^t = \boldsymbol{f}^t \boldsymbol{L}^t \boldsymbol{y}^t \tag{1}$$

where $\mathbf{f}^t$ is the $1 \times n$ row vector of emission intensities (CO_2 per unit output) in period t, $\mathbf{A}^t$ is the $n \times n$ matrix of direct input coefficients in t, $\mathbf{L}^t = (\mathbf{I} - \mathbf{A}^t)^{-1}$is the Leontief inverse, capturing total direct and indirect requirements per unit of final demand, and $\mathbf{y}^t$ is the $n \times 1$ final demand vector. The change in emissions between the two periods is

$$\Delta C = C^1 - C^0 \tag{2}$$

Final demand is disaggregated into major components:

$$\mathbf{y}^t = \mathbf{y}^{H,t} + \mathbf{y}^{G,t} + \mathbf{y}^{I,t} + \mathbf{y}^{X,t} \tag{3}$$

With $\mathbf{y}^{H,t}$represents household expenditure, $\mathbf{y}^{G,t}$ government expenditure, $\mathbf{y}^{I,t}$ investment or gross capital formation, and $\mathbf{y}^{X,t}$introduces as exports. This decomposition aligns with conventional SDA frameworks that partition economic demand into key behavioural categories.

2.1.2 Additive Shapley SDA with final demand components

The Shapley-based Structural Decomposition Analysis (SDA) allocates changes in sectoral CO_2 emissions to six distinct drivers, ensuring fair, path-independent decomposition (Albrecht et al. 2002). The total CO_2 emissions for sector $i$at time $t$are given by:

$$C_i^{(t)} = f_i^{(t)} \sum_{j=1}^{n} L_{ij}^{(t)} \left(Y_{H,j}^{(t)} + Y_{G,j}^{(t)} + Y_{I,j}^{(t)} + Y_{X,j}^{(t)}\right), \tag{4}$$

where $f_i^{(t)}$is the CO_2 intensity of sector i, $L^{(t)}$is the Leontief inverse matrix, and Y_H, Y_G, Y_I, and $Y_X$are the household, government, investment, and export final demand vectors, respectively. The Shapley value contribution of factor $k(f, L, Y_H, Y_G, Y_I, Y_X)$ to the change in sectoral emissions from year 0 to year 1 is computed as the average marginal effect across all permutations of factors:

$$\phi_{i,k} = \frac{1}{|\ \mathrm{Perm}(F)\ |} \sum_{p \in \mathrm{Perm}(F)} [\ C_i(\text{factor } k \text{ at year 1, others at state in permutation } p) - C_i(\text{previous state in permutation } p)],$$

where $\mathrm{Perm}(F)$is the set of all $6! = 720$ permutations of the six factors. In this framework, the *CO_2 intensity effect* $(\phi_{i,f})$ reflects changes in emission intensities; the *technology effect* $(\phi_{i,L})$ captures shifts in intersectoral production linkages; the *household, government, and investment effects* $(\phi_{i,Y_H}, \phi_{i,Y_G}, \phi_{i,Y_I})$ measure changes in domestic final demand; and the *exports effect* (ϕ_{i,Y_X}) represents changes in foreign demand. By construction, the sum of all six components exactly equals the total change in sectoral emissions.

$$\Delta C_i = C_i^{(1)} - C_i^{(0)} = \phi_{i,f} + \phi_{i,L} + \phi_{i,Y_H} + \phi_{i,Y_G} + \phi_{i,Y_I} + \phi_{i,Y_X} \quad (5)$$

This approach allows for a precise attribution of emission changes to both production- and demand-side drivers, providing a transparent and comprehensive understanding of the factors underlying sectoral CO_2 emissions.

2.2 Linking SDA features to machine learning (ML) models

Based on equation (5), we define the driver vector:

$$\mathbf{z}_{it} = (\phi_{i,f}, \phi_{i,L}, \phi_{i,Y_H}, \phi_{i,Y_G}, \phi_{i,Y_I}, \phi_{i,Y_X}, \mathbf{w}_{it}) \quad (6)$$

Define w_{it}as a vector of sectoral-level covariates that are consistent with I-O data. Hence, at the sectoral level, emissions are modelled as

$$y_{it} = g\,(\mathbf{z}_t, \mathbf{w}_{it}) + \varepsilon_{it}$$

Here, g represents the unknown mapping from drivers to emissions and ε_{it} denotes the residual noise. Estimating g is central to identifying the factors that consistently drive sectoral emissions. In this framework, y_{it} corresponds to sector-level direct or indirect CO_2 emissions, z_t captures economy-wide structural changes as identified through the SDA, and w_{it} accounts for sector-specific heterogeneity within the input–output system. To assess the stability and predictive power of both aggregated and sectoral rankings of emission drivers, as noted in the Introduction, we applied a combination of Neural Networks with SHAP, Lasso, Elastic Net, and Bayesian regression. This ensemble approach provides complementary perspectives on feature importance and stability, leveraging the strengths of each method in the context of small, high-dimensional SDA datasets.[1]

2.2.1 Neural network with SHAP value

Nonlinearities and interactions are inherent in the economic systems. For instance, the effect of changes in final demand consumption, ϕ_{i,Y_H}, may depend on sectoral output, sectoral demand, and intersectoral interactions represented in the Leontief matrix. To capture these complex relationships, we employed a feed-forward neural network that can model nonlinear dependencies and interactions between multiple drivers simultaneously.

$$\mathbf{h}_{it}^{(l)} = \sigma(\mathbf{W}^{(l)}\mathbf{h}_{it}^{(l-1)} + \mathbf{b}^{(l)}), l = 1, \dots, L$$

1. We employ four complementary models to assess SDA feature importance. A neural network with SHAP captures nonlinearities and interactions, with SHAP values providing additive and consistent feature attributions (Lundberg & Lee, 2017). Lasso regression identifies dominant predictors via L1 regularization, enforcing sparsity and reducing overfitting (Tibshirani, 1996). Elastic Net combines L1 and L2 penalties to preserve groups of correlated features, which is important when SDA drivers co-vary (Zou & Hastie, 2005). Bayesian regression incorporates prior information and produces posterior distributions, thereby quantifying uncertainty in feature importance (Gelman et al., 2013). Collectively, these methods provide a robust and interpretable assessment of feature importance across nonlinear, sparse, correlated, and uncertain settings.

with output:

$$\hat{y}_{it} = \mathbf{W}^{(L+1)}\mathbf{h}_{it}^{(L)} + b^{(L+1)}.$$

where $\mathbf{h}_{it}^{(l)}$ are hidden-layer activations; $\mathbf{W}^{(l)}, \mathbf{b}^{(l)}$ are learnable weights and biases, and σ is a nonlinear activation. To make the neural network interpretable, we used SHapley Additive exPlanations (SHAP):

$$\hat{y}_{it} = \phi_0 + \sum_{k=1}^{K_z} \phi_{k,t}^{(z)} + \sum_{m=1}^{K_w} \phi_{m,it}^{(w)}; \phi_j = \sum_{S\subseteq F\setminus\{j\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[g(S \cup \{j\}) - g(S)]$$

$\phi_{k,t}^{(z)}$ quantifies the contribution of SDA driver z_t, and $\phi_{m,it}^{(w)}$ quantifies the contribution of sectoral covariate w_{it}. This approach ensures a fair allocation of contributions, even among correlated features (Lundberg & Lee, 2017), and enables the identification of stable, high-impact SDA drivers, including in high-dimensional and nonlinear settings. In practical terms, a large positive SHAP value for the CO_2 intensity effect in a given sector-year indicates that changes in emission intensity were the primary reason the model predicted higher (or lower) emissions for that observation, holding all other drivers constant.

2.2.2 Lasso and elastic net regression

Lasso imposes L1 regularization as a technique used in regression and other machine learning models to shrink coefficients and perform feature selection.

$$\min_{\boldsymbol{\beta},\boldsymbol{\gamma}} \frac{1}{2nT}\sum_{i,t}(y_{it} - \alpha - \mathbf{z}_t^\top\boldsymbol{\beta} - \mathbf{w}_{it}^\top\boldsymbol{\gamma})^2 + \lambda\sum_j |\theta_j|,$$

where $\theta_j \in \{\beta_k, \gamma_m\}$.

Lasso emphasizes sparsity by identifying the most influential features while simultaneously performing automatic variable selection (Tibshirani, 1996). This property is particularly useful for small datasets because it helps prevent overfitting and improves model interpretability. Elastic Net extends Lasso by combining L1 (absolute value) and L2 (squared) regularization in a single framework. Mathematically, the Elastic Net minimizes

$$\min_{\boldsymbol{\beta},\boldsymbol{\gamma}} \frac{1}{2nT}\sum_{i,t}(y_{it} - \alpha - \mathbf{z}_t^\top\boldsymbol{\beta} - \mathbf{w}_{it}^\top\boldsymbol{\gamma})^2 + \lambda[\alpha_1\sum_j |\theta_j| + (1-\alpha_1)\sum_j \theta_j^2].$$

While Lasso may arbitrarily select one predictor among several correlated variables, Elastic Net preserves groups of correlated SDA drivers, which is particularly important when economic variables co-vary (Zou & Hastie, 2005).

2.2.3 Bayesian regression

Bayesian linear regression incorporates uncertainty in coefficient estimation by treating each model parameter as a probability distribution rather than as a fixed value. Using prior information and observed data, it computes posterior distributions for the coefficients, allowing for probabilistic inference about feature importance and quantifying uncertainty in predictions (Gelman et al., 2013).

$$y_{it} \mid \boldsymbol{z}_t, \boldsymbol{w}_{it}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \sigma^2 \sim \mathcal{N}(\alpha + \boldsymbol{z}_t^\top\boldsymbol{\beta} + \boldsymbol{w}_{it}^\top\boldsymbol{\gamma}, \sigma^2)$$

with priors:

$$\boldsymbol{\beta} \sim \mathcal{N}(0, \tau_z^2\boldsymbol{I}), \boldsymbol{\gamma} \sim \mathcal{N}(0, \tau_w^2\boldsymbol{I}), \sigma^2 \sim \text{Inverse-Gamma(a, b)}.$$

This approach is particularly valuable for small datasets, where conventional point estimates may be unstable and less reliable (Gelman et al., 2013).

2.2.4 Bootstrap-based stability and predictability

To evaluate feature stability and predictive robustness, we generated $B = 30$ bootstrap resamples of the training data set[2]. Each resample was drawn with replacement, and all models, including the Neural Network, Lasso, Elastic Net, and Bayesian regression, were retrained on each bootstrap iteration. Feature importance metrics were then extracted from each iteration to assess the consistency and reliability of the driver rankings across the resamples.

$$I_{f,m}^{(b)} = \begin{cases} \phi_{f,it}^{(b)}, & \text{NN-SHAP} \\ \hat{\beta}_f^{(b)}, & \text{Lasso} \\ \hat{\theta}_f^{(b)}, & \text{Elastic Net} \\ \mathbb{E}[\beta_f^{(b)}], & \text{Bayesian} \end{cases}, b = 1, \dots, B$$

f indexes features (drivers or covariates); m indexes models; $\phi_{f,it}^{(b)}$ are SHAP values for neural networks; $\hat{\beta}_f^{(b)}$ and $\hat{\theta}_f^{(b)}$ are coefficients for linear models, and $\mathbb{E}[\beta_f^{(b)}]$ is the posterior mean in Bayesian regression. We assessed feature stability across bootstrap resamples using two complementary metrics: median rank and coefficient of variation (CV). For each feature f and model m, the median rank is computed as

$$\text{MedianRank}_{f,m} = \text{median}(\text{rank}(-I_{f,m}^{(b)})), b = 1, \dots, B,$$

where $I_{f,m}^{(b)}$ is the feature importance in bootstrap b. The CV measures relative variability:

$$\text{CV}_{f,m} = \frac{\text{SD}(I_{f,m}^{(1)}, \dots, I_{f,m}^{(B)})}{\bar{I}_{f,m}}, \bar{I}_{f,m} = \frac{1}{B}\sum_{b=1}^{B} I_{f,m}^{(b)}.$$

Features with low CV and high median ranks are considered stable and robust, whereas a high CV indicates sensitivity to resampling. We also evaluated whether feature importance based on measured $I_{f,m}^{(b)}$ is predictable across bootstraps. For each feature f, we define as

$$I_f^{(b)} = h_f(\mathbf{x}^{(-b)}) + \epsilon,$$

where $\mathbf{x}^{(-b)}$ is the input feature from all other bootstraps. For neural networks, $I_f^{(b)} = \phi_{f,it}^{(b)}$ (SHAP values), and for linear or Bayesian models, $I_f^{(b)}$ corresponds to standardized or posterior coefficients. Predictable importance indicates that the model consistently identifies the same SDA drivers across resamples, enhancing confidence in their reproducibility. Unpredictable importance suggests that the apparent influence of some features may depend heavily on sampling variability. In practical terms, a driver with a low CV and a consistently high median rank reliably matters across different data samples, providing a stronger basis for policy intervention than one whose ranking fluctuates with the sample.

2. While larger values of B can increase precision, empirical studies suggest that $B \approx 25$–50 is sufficient for robust assessment of ranking and variability metrics in small datasets (Efron & Tibshirani, 1994). Our choice of $B = 30$ represents a practical balance between computational feasibility and reliable estimation of feature stability across models.

3. Results and discussion

In this study, we use Malaysia's I-O tables at constant 2010 prices for the period 2010–2020, obtained from the Asian Development Bank (ADB, 2020). The I-O tables include 35 industries and five final demand categories and are expressed in 2010 prices by deflating the current-price tables using implicit price indices (deflators). Sectoral production-based CO_2 emissions were used as environmental data, measured in million tonnes of CO_2-equivalent. These data are available in aggregated form for 15 economic sectors from the Organisation for Economic Co-operation and Development (OECD, 2025).

Owing to the limited availability of CO_2 emission data for more disaggregated subsectors, the 35-sector I–O tables for Malaysia were aggregated into 15 sectors to ensure compatibility with the sectoral CO_2 emissions data. This aggregation enabled consistent alignment between the economic and environmental datasets for subsequent SDA and ML analyses. Data cleaning and preparation were performed using Excel, and SDA and ML analyses were conducted using R.

3.1 Carbon emission drivers of Malaysia

Table 1 presents the year-on-year SDA results. Three analytically important patterns emerged over the decade. First, intensity-led mitigation dominated the early period (2010–2012): the CO_2 intensity effect delivered the largest net emission reductions, reflecting efficiency gains and early fuel switching. Second, demand-driven pressures prevailed in the mid-decade (2013–2018), as household and export effects progressively offset intensity improvements, consistent with Malaysia's sustained GDP expansion. Third, the pandemic year (2019–2020) constitutes a structural outlier with extreme cross-driver swings that should be interpreted cautiously for long-run policy extrapolations. Within this overall picture, the 2019–2020 period featured the most extreme individual contributions, driven by COVID-19 disruptions. The large positive *technology effect* (+34.829 Mt) likely reflects shifts in production structures and intermediate input requirements amid global supply chain interruptions, including factory closures and changes in input sourcing patterns (Sun & Mi, 2023). Meanwhile, the high negative *household effect* (-26.824 Mt) and substantial negative *export effect* (-13.527 Mt) align with lockdown-induced collapses in consumer spending and international trade volumes, which significantly reduced demand-driven emissions (Le Quéré et al. 2020; Liu et al. 2020). Early in the decade, the *CO_2 intensity effect* showed the deepest negative contributions, particularly in 2010-2011 and 2011-2012. These reflect periods of notable progress in decarbonizing energy supply and production processes, consistent with broader trends in efficiency gains and fuel switching during the early 2010s (Guan, D., et al. 2018; Zheng, X., et al. 2020).

Table 1: Yearly contributions of structural decomposition effects to changes in CO_2 emissions, 2010–2020 (million tone Co2 equivalent)

Period	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2010–2011	-24.053	-5.365	4.717	2.190	1.978	6.521
2011–2012	-21.062	6.061	9.490	0.849	2.805	-3.404
2012–2013	7.198	-0.980	9.118	0.833	-0.124	-0.994
2013–2014	3.503	-4.455	8.176	0.763	-0.276	4.812
2014–2015	-13.069	-0.240	11.025	-0.229	3.311	-1.648
2015–2016	-19.994	1.508	8.062	0.092	2.947	2.347
2016–2017	1.917	-11.522	7.076	0.770	0.815	0.000
2017–2018	-16.183	-1.293	13.124	0.480	-0.509	20.969
2018–2019	-8.821	3.339	12.967	0.264	-2.128	-1.046
2019–2020	-4.655	34.829	-26.824	0.363	-2.184	-13.527

The *household effect* reached its highest positive levels in 2017-2018 and 2018-2019. This indicates strong emission pressures from rising household consumption during a phase of robust economic expansion in many regions, such as China, before 2017 (Mi et al. 2016). The *export effect* achieved its peak positive contribution in 2017-2018 (+20.969 Mt). This highlights a year of particularly intense trade-related emission growth, driven by the heightened global demand for exported goods and services. In comparison, the *government effect* and *investment effect* consistently display smaller magnitudes across all periods. This suggests that these drivers played more limited roles in generating major year-to-year emission fluctuations relative to intensity, technology, household, and export factors. These patterns, especially the pandemic anomalies in 2019–2020, strong intensity reductions in the early 2010s, and elevated demand-side positives in 2017-2018; capture the dominant influences on emission changes over the decade.

The yearly sectoral contributions, as shown in Table 2, reveal the electricity, gas, and water supply sector (S4) as the dominant driver of CO_2 emission fluctuations across the decade, delivering the largest reductions in 2010-2011 and substantial increases in 2016-2017 and 2019-2020. Manufacturing (S3) emerged as a key amplifier of emission growth, particularly through its peak contribution in 2017-2018, while also contributing to reductions during the pandemic (COVID-19) year. Wholesale and retail trade (S6) and Transportation & Storage (S8) show pronounced variability, acting as major sources of emission increases in 2012–2013 and 2017-2018 but driving sharp reductions in 2019-2020 due to demand collapses.

Table 2: Yearly sectoral total contributions to CO_2 emission changes (2010–2020)

ID	Sector Name	2010-11	2011–12	2012–13	2013–14	2014–15	2015–16	2016–17	2017–18	2018–19	2019–20
S1	Agriculture, hunting, forestry	-1.643	-0.736	0.851	-0.785	-0.038	0.500	0.172	0.969	-0.137	-1.346
S2	Mining and quarrying	-0.868	-2.193	1.036	4.273	-0.953	-6.121	-8.096	0.514	0.123	3.938
S3	Manufacturing	0.000	2.246	-5.506	0.813	1.168	2.110	1.592	10.382	-0.557	-5.349
S4	Electricity, gas, and water supply	-11.157	-1.941	2.681	3.924	0.303	0.122	11.172	1.914	1.169	16.047
S5	Construction	0.000	0.299	-0.249	-0.043	0.023	0.071	0.219	0.291	-0.029	-0.227
S6	Wholesale and retail trade	-1.378	-2.758	7.665	1.438	-1.518	0.878	-3.931	1.772	2.128	-12.885
S7	Hotels and restaurants	0.246	-0.089	0.287	0.136	-0.186	0.201	-0.178	-0.090	0.154	-0.391
S8	Transportation and Storage	1.291	-0.165	7.064	2.895	-0.085	-0.121	-1.472	1.794	1.349	-10.114
S9	Information and communication	0.053	0.040	0.123	0.084	0.109	0.048	-0.050	-0.038	0.043	-0.119
S10	Financial intermediation	-0.141	-0.027	0.024	-0.013	0.008	0.030	-0.026	-0.055	0.030	-0.024
S11	Real estate activities	0.408	0.345	0.769	0.594	0.888	0.260	-0.214	0.124	0.183	-0.727
S12	Public administration activities	0.181	0.035	0.217	0.074	0.062	0.095	0.002	-0.040	0.123	-0.343
S13	Education	0.060	-0.029	0.048	-0.015	-0.028	0.044	-0.021	-0.088	0.042	-0.039
S14	Health and social work activities	0.052	0.010	0.057	0.040	-0.025	0.043	-0.025	-0.040	0.037	-0.027
S15	Other service activities	0.050	0.057	0.226	0.150	-0.019	0.104	-0.056	-0.008	0.080	-0.218

Mining and quarrying (S2) provides significant mitigation in the mid-decade years, especially 2015-2016 and 2016-2017, whereas agriculture (S1) plays a smaller and more episodic role. The 2017-2018 period stands out as the decade's strongest emission growth phase, led by manufacturing (S3) and supported by electricity (S4), wholesale and retail trade (S6), and transportation and storage (S8). In contrast, 2019-2020 records the deepest reductions, dominated by negative contributions from wholesale and retail trade (S6), transportation and storage (S8), and manufacturing (S3), partially offset by the positive restructuring effect of electricity. The service sectors (S9 to S15) consistently show negligible net impacts throughout all periods, confirming that emission dynamics are overwhelmingly concentrated in electricity supply (S4), manufacturing (S3), wholesale and retail trade (S6), transportation and storage (S8), and mining (S2). Detailed breakdowns of each effect by sector and year are provided in *Appendix A*, allowing for a detailed examination of the specific mechanisms underlying these net sectoral contributions to the economy.

3.2 Carbon emission drivers ranking

Table 3 presents a comparative assessment of feature importance for the six SDA effects driving CO_2 emission changes, derived from four complementary methods: SHAP (mean absolute value), Lasso regression (mean absolute coefficient), Elastic Net regression, and Bayesian ridge regression. As noted in the methodology section, SHAP provides a model-agnostic measure of global feature impact, whereas the regression-based approaches reflect average coefficient magnitudes across fitted models. This multi-method evaluation helps validate the relative influence of each driver and reveals the nuances of how linear versus nonlinear interpretations rank the effects.

Table 3: Feature importance rankings across four ML approaches

Feature	SHAP Mean	SHAP Rank	Lasso Mean	Lasso Rank	ElasticNet Mean	ElasticNet Rank	Bayesian Mean	Bayesian Rank
CO_2 Intensity Effect	231.81	1	3.021	3	3.022	3	3.126	3
Technology Effect	153.94	2	3.904	1	3.916	1	4.194	1
Household Effect	105.91	3	3.032	2	3.023	2	3.230	2
Government Effect	68.48	4	0.109	6	0.122	6	0.156	6
Investment Effect	23.49	5	0.234	5	0.239	5	0.256	5
Export Effect	14.24	6	0.982	4	0.984	4	0.993	4

The multi-method comparison in Table 3 provides two key analytical insights. First, the convergence across SHAP, Lasso, Elastic Net, and Bayesian rankings provides strong cross-validation: when methodologically distinct models agree on a ranking, the finding is unlikely to be an artefact of any estimation approach. Second, the divergence between SHAP and the linear models on the top-ranked driver (CO_2 intensity vs. technology effect) is informative in itself; it suggests that the influence of CO_2 intensity is partly nonlinear and context-dependent, a nuance that linear regularisation methods inherently underweight. Specifically, the CO_2 intensity effect emerged as the most influential feature under SHAP by a considerable margin, reflecting its large and variable contributions to the model predictions. The technology effect ranked first in all three regression methods and second in SHAP, confirming its robust role in explaining emission fluctuations. The household effect maintains a solid second or third position throughout, underscoring the importance of household demand as a stable demand-side driver. In contrast, the government, investment, and export effects are uniformly ranked as the least important, with particularly small coefficients in the linear models which present their limited explanatory power relative to supply-side and major demand-side factors. This convergence across diverse methodologies reinforces the primary conclusions of the decomposition analysis: emission changes are predominantly shaped by CO_2 intensity improvements, production technology shifts and household consumption patterns.

The bar chart in Figure 1 visualises the same feature importance rankings presented in the table, using a horizontally grouped bar format to compare the four methods side-by-side for each SDA effect. The x-axis represents the rank (from 0 to 6, where lower numbers indicate higher importance), and the y-axis lists the six features in descending order of overall significance. The chart effectively illustrates the high agreement among methods on the relative ordering of the drivers-particularly the top three (CO_2 intensity, technology, household) and bottom three (government, investment, export)-while highlighting methodological differences: SHAP elevates CO_2 intensity dramatically, whereas linear models prioritize the technology effect. This convergence reinforces the robustness of the core findings regarding the SDA effects that most strongly influence CO_2 emission changes.

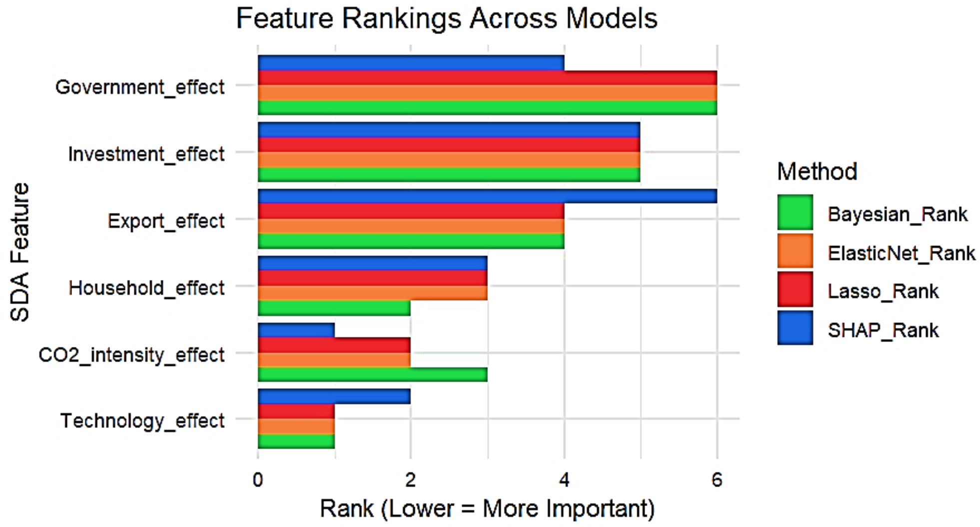

Figure 1: Feature Importance Rankings of SDA Effects Across Different Models

Based on the four models employed in this study, SHAP proves to be an effective method for ranking feature importance because it captures both the magnitude and variability of each feature's contribution to model predictions. The SHAP median ranks, summarized in Table 4, show reasonable stability (CVs 0.27–0.42), indicating that the rankings are generally consistent while still reflecting meaningful differences in influence across observations. For example, *Technology_effect* exhibits the highest CV (0.424), indicating that its importance varies depending on the context, which highlights SHAP's ability to detect interaction effects and nonlinear relationships that linear methods such as Lasso or ElasticNet may overlook. This sensitivity ensures that features with context-dependent impacts are appropriately recognized, making the SHAP rankings both informative and nuanced. Overall, SHAP provides a theoretically grounded, interaction-aware, and empirically justified approach for ranking features in this dataset.

Table 4: Feature *median* ranks and coefficients of variation (CV)

Feature	SHAP_M	Lasso_M	ElasticNet_M	Bayesian_M	CV (SHAP)	CV (Lasso)	CV (ElasticNet)	CV (Beysian)
CO2_intensity_effect	1	3	3	3	0.271	0.011	0.010	4.40E-07
Technology_effect	2	1	1	1	0.424	0.029	0.029	1.13E-06
Household_effect	3	2	2	2	0.357	0.035	0.034	8.57E-07
Government_effect	4	6	6	6	0.296	0.509	0.449	1.90E-05
Investment_effect	5	5	5	5	0.267	0.058	0.054	2.68E-06
Export_effect	6	4	4	4	0.395	0.029	0.028	9.58E-07

3.3 SHAP values of carbon emission drivers ranking

We further assessed the relative importance and directional impacts of the six SDA effects using SHAP values derived from four machine learning models (Neural Network, Lasso, Bayesian Linear, and Elastic Net). This multi-model approach not only identifies the most influential drivers of CO_2 emission changes but also reveals their stability across different modelling frameworks, as shown in Figure 2. SHAP summary plots (beeswarm plots) are employed to visualise the global impact of each SDA effect across all sector-year observations. In these plots, each point represents one sector-year instance, positioned horizontally by its SHAP value (positive values increase predicted emissions, negative values decrease them) and coloured by the feature value (red = high, blue = low). The features are ordered vertically by overall importance (those at the top exhibit the widest SHAP distributions and the largest median absolute impacts).

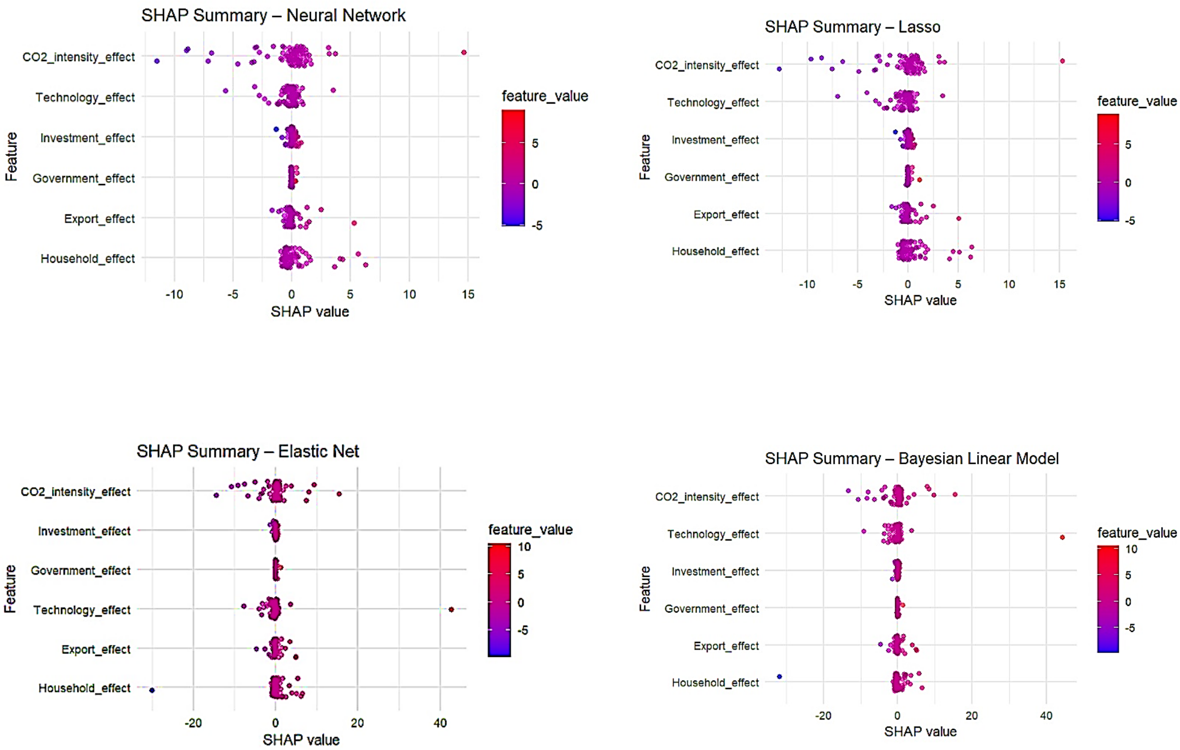

Figure 2: Feature Importance Rankings of SDA Effects Across Different Models Based on SHAP values

Across all four models, the CO_2 intensity effect consistently emerged as the most influential driver. It has the broadest SHAP value spread and dense clustering, higher intensity values (red points), and predominantly produces strong negative SHAP values. The technology effect ranks closely behind, with wide distributions typically shifted toward negative impacts for higher values, highlighting production structure changes as a key mitigating driver. The household effect maintained a substantial influence and showed dense clusters of mostly negative SHAP values with some variability. This demonstrates the tangible carbon impact of everyday consumption activities. In contrast, the export, investment, and government effects exhibit narrowly clustered distributions near zero across all models which represent their stability minor role. This convergence reinforces the stability of the findings: emission dynamics are predominantly governed by CO_2 intensity, technology, and household effects, with the remaining demand components contributing only marginally over time and across sectors.

3.4 Sectoral carbon emission drivers ranking

The SHAP-based sector ranking in Table 5 reveals the overall influence of Malaysia's 15 sectors on CO_2 emissions (2010–2020), measured by the sum of the average absolute SHAP values across the six SDA drivers. Higher values indicate a greater driver impact on the predicted sectoral emissions.

Table 5: Total SHAP values for each Sector

Rank	Sector ID	Sector Name	Total SHAP Value
1	S4	Electricity, gas, and water supply	8.511
2	S7	Hotels and restaurants	7.260
3	S9	Information and communication	6.833
4	S6	Wholesale and retail trade	4.962
5	S14	Health and social work activities	4.796
6	S10	Financial intermediation	4.135
7	S8	Transportation and Storage	3.267
8	S11	Real estate activities	3.080
9	S13	Education	3.040
10	S12	Public administration, and professional activities	2.487
11	S3	Manufacturing	2.423
12	S15	Other service activities	2.272
13	S2	Mining and quarrying	1.854
14	S1	Agriculture, hunting, forestry, and fishing	1.848
15	S5	Construction	1.617

The Electricity, gas, and water supply sector (S4) topped the list (8.511), reflecting its fossil fuel dominance. Hotels and restaurants (S7, 7.260) and information and communication (S9, 6.833) follow, driven by energy-intensive tourism and digital infrastructure. Mid-ranked sectors such as wholesale and retail trade (S6), health and social work activities (S14), and financial intermediation (S10) show moderate demand-side influence, while lower-ranked sectors, including manufacturing (S3), agriculture (S1), mining (S2), and construction (S5), exhibit lesser variability. Across sectors, Figure 3 indicates that the technology and CO_2-intensity effects exert the strongest influence across sectors, with substantially larger absolute SHAP values than the other components. Sector 4 shows the most pronounced technology effect overall, and Sectors S7 and S9 show major CO_2-intensity effects. These patterns highlight the central roles of innovation and emissions efficiency.

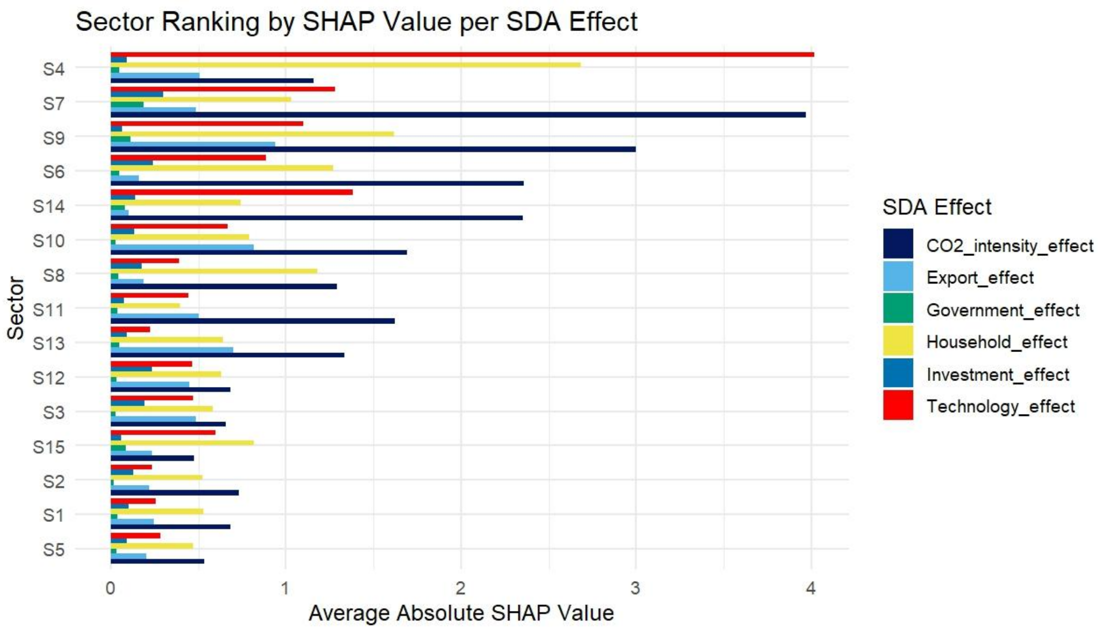

Figure 3. SHAP-Based Ranking of SDA Effects at the Sector Level

The Household effect is meaningful but more evenly distributed across sectors and never reaches the magnitude of the top two effects. Export, Investment, and Government effects remain relatively weak across the sector ranking, suggesting limited explanatory power. Overall, only a small group of sectors-primarily S4, S7, S9, S14, S10, and S6-absorb most of the decomposition influence, while the remaining sectors appear far less responsive to these drivers.

4. Conclusion and policy recommendations

This study employs structural decomposition analysis (SDA) integrated with machine learning techniques to dissect the drivers of CO_2 emissions in Malaysia from 2010 to 2020. The results reveal that the CO_2 intensity, technology, and household effects are the most influential and stable factors across aggregate and sectoral levels, as consistently ranked by SHAP, Lasso, Elastic Net, and Bayesian Regression methods (Lundberg & Lee, 2017; Tibshirani, 1996; Zou & Hastie, 2005; Gelman et al., 2013). The analysis underscores the dominance of sectors such as electricity, gas, and water supply (S4), manufacturing (S3), wholesale and retail trade (S6), and transportation and storage (S8) in driving emission fluctuations, with notable patterns including early decade intensity reductions, mid-decade growth from demand-side pressures, and pandemic-induced declines in 2019-2020 (Guan et al., 2018; Le Quéré et al., 2020). This novel hybrid ML-SDA approach not only identifies key drivers but also evaluates their predictability, offering a robust framework for emissions research that extends beyond traditional methodologies (Su & Ang, 2017; De Boer & Rodrigues, 2020). By providing evidence-based insights into emission dynamics in a developing economy such as Malaysia, the findings contribute significantly to global climate mitigation efforts, aligning directly with SDG 13 (Climate Action) by enhancing policy planning and sustainable development tools (IPCC, 2023; Sandu et al., 2019).

This study makes three distinct contributions to the literature. Methodologically, it introduces a hybrid ML-SDA framework that extends decomposition analysis from driver identification to driver stability and predictability assessment, a novel combination that is rarely applied in the emissions literature. Empirically, it delivers the first systematic ML-validated ranking of CO_2 drivers for Malaysia using multi-year input-output data, addressing a gap in ASEAN-specific research on decomposition. Analytically, the cross-method convergence of the four ML approaches (SHAP, Lasso, Elastic Net, Bayesian) on a consistent driver hierarchy strengthens credibility beyond what any single-method study could achieve. To strengthen Malaysia's alignment with SDG 13 (Climate Action), policymakers should prioritize targeted interventions in the most stable and predictable emission drivers identified in this study, including CO_2 intensity reductions, technological shifts in production structures, and household consumption patterns, while focusing on high-impact sectors such as electricity, gas, and water supply (S4), manufacturing (S3), wholesale and retail trade (S6), and transportation and storage (S8).

Accelerating decarbonization in the electricity and manufacturing sectors through renewable energy adoption and efficiency upgrades should be integrated into the National Energy Transition Roadmap (NETR) (Ministry of Economy, 2023) and the National Policy on Climate Change 2.0 (Ministry of Natural Resources and Environmental Sustainability, 2024), with enhanced incentives under the extended Green Technology Financing Scheme. Technological innovation can be promoted through investments in clean production and circular economy practices through the New Industrial Master Plan 2030 (NIMP 2030) (Ministry of Investment, Trade and Industry, 2023), which emphasizes sustainable supply chains in energy-intensive industries. On the demand side, managing household consumption as a stable driver requires nationwide campaigns for sustainable lifestyles, coupled with subsidies for low-carbon products and the phased implementation of the carbon tax introduced in 2026, initially targeting high-emission sectors to internalize environmental costs while supporting a just transition measures.

Additionally, incorporating carbon border adjustments into trade policies and green investment criteria will address minor but growing export-related emissions, aligning with priorities for resilient growth and net-zero ambitions under the ongoing Thirteenth Malaysia Plan (2026-

2030) (Economic Planning Unit, 2025). These evidence-based recommendations, grounded in the ML-SDA analysis and informed by insights from Malaysia's Third Voluntary National Review (2025) (Ministry of Economy, 2025), provide a foundation for actionable climate-change strategies. Operationalizing these policy recommendations requires a structured, phased approach to ensure effective implementation and measurable progress toward SDG 13.

The implementation of these recommendations should be structured around three phases aligned with Malaysia's existing planning cycles: (1) Short-term (2026–2027): update GHG inventories, integrate SDA-identified priority sectors into NETR decarbonisation targets, and launch carbon tax enforcement in electricity (S4) and manufacturing (S3); (2) Medium-term (2027–2030): scale renewable transitions, enforce updated efficiency regulations, and embed household consumption reduction metrics into the Thirteenth Malaysia Plan monitoring framework; and (3) Long-term (post-2030): institutionalise climate literacy, leverage green bonds and international climate finance, and conduct adaptive policy reviews using updated SDA-ML analyses. This phased approach aligns with Malaysia's Paris Agreement commitments and the Third Voluntary National Review (2025). This integrated approach ensures that policy recommendations translate into tangible outcomes, driving Malaysia toward net-zero, and equitable climate resilience by 2050.

Nevertheless, this study has several limitations that should be addressed in future research. First, the analysis is constrained to 2010–2020 by data availability; extending it to post-pandemic years (2021–2024) would test whether the identified stable drivers hold under new structural conditions. Second, sector aggregation from 35 to 15 industries, necessitated by CO_2 data availability, may mask the within-group heterogeneity. Third, while the bootstrap procedure (B=30) mitigates small-sample concerns, larger datasets would enable more complex neural architectures and stronger out-of-sample validations. Fourth, production-based emission accounting does not fully capture Malaysia's carbon responsibility; future work should integrate consumption-based MRIO approaches. Building on these foundations, future studies could extend the hybrid ML-SDA framework using consumer psychology models (e.g. structural equation modelling) to validate the causal pathway from household behaviour to CO_2 emissions and conduct cross-country comparisons across ASEAN economies to yield culturally differentiated policy recommendations.

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Appendix A

Table I.1: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2010–2011

Period	Sector_ID	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2010–2011	S1	Agriculture, hunting, forestry, and fishing	-2.566	-0.378	0.595	0.047	0.220	0.439
2010–2011	S2	Mining and quarrying	-1.354	-0.340	0.234	0.047	0.292	0.253
2010–2011	S3	Manufacturing	-2.828	-0.218	0.980	0.174	0.394	1.499
2010–2011	S4	Electricity, gas, and water supply	-14.113	-3.881	1.992	1.446	0.494	1.906
2010–2011	S5	Construction	-0.311	-0.070	0.008	0.012	0.184	0.011
2010–2011	S6	Wholesale and retail trade	-3.386	-0.315	0.529	0.146	0.255	1.393
2010–2011	S7	Hotels and restaurants	0.176	-0.017	0.032	0.009	0.001	0.046
2010–2011	S8	Transportation and Storage	-0.147	-0.108	0.307	0.160	0.129	0.949
2010–2011	S9	Information and communication	0.054	-0.006	0.001	0.001	0.000	0.003
2010–2011	S10	Financial intermediation	-0.140	-0.013	0.005	0.002	0.002	0.004
2010–2011	S11	Real estate activities	0.388	-0.003	0.005	0.003	0.005	0.010
2010–2011	S12	Public administration and professional activities	0.138	-0.012	-0.002	0.055	-0.000	0.001
2010–2011	S13	Education	0.016	-0.001	-0.007	0.051	0.000	0.002
2010–2011	S14	Health and social work activities	0.025	-0.002	-0.004	0.031	0.000	0.002
2010–2011	S15	Other service activities	-0.005	-0.000	0.042	0.008	0.002	0.004

Table I.2: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2011–2012

Period	Sector_ID	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2011–2012	S1	Agriculture, hunting, forestry, and fishing	0.703	0.255	-0.324	0.019	-0.259	-0.470
2011–2012	S2	Mining and quarrying	-3.706	0.703	0.325	0.018	0.319	0.148
2011–2012	S3	Manufacturing	0.956	0.544	1.385	0.071	0.768	-1.477
2011–2012	S4	Electricity, gas, and water supply	-13.349	4.020	6.205	0.548	0.786	-1.147
2011–2012	S5	Construction	-0.169	0.031	0.019	0.005	0.417	-0.005
2011–2012	S6	Wholesale and retail trade	-4.008	0.176	1.143	0.054	0.357	-0.480
2011–2012	S7	Hotels and restaurants	-0.142	-0.003	0.054	0.004	0.002	-0.007
2011–2012	S8	Transportation and Storage	-1.581	0.330	0.597	0.069	0.391	0.031
2011–2012	S9	Information and communication	0.040	-0.013	0.007	0.000	0.000	0.005
2011–2012	S10	Financial intermediation	-0.025	-0.006	0.004	0.000	0.002	-0.002
2011–2012	S11	Real estate activities	0.312	0.002	0.017	0.002	0.016	-0.002
2011–2012	S12	Public administration and professional activities	-0.012	0.008	0.004	0.034	0.002	0.000
2011–2012	S13	Education	-0.072	0.002	0.025	0.016	0.000	0.001

2011–2012	S14	Health and social work activities	-0.038	0.004	0.016	0.007	0.000	0.001
2011–2012	S15	Other service activities	0.029	0.008	0.015	0.003	0.003	0.000

Table I.3: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2012–2013

Period	Sector_ID	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2012–2013	S1	Agriculture, hunting, forestry, and fishing	0.987	-0.315	0.836	0.019	-0.789	-0.105
2012–2013	S2	Mining and quarrying	0.152	0.549	0.213	0.019	0.243	-0.140
2012–2013	S3	Manufacturing	-6.039	-0.412	0.851	0.069	-0.049	0.054
2012–2013	S4	Electricity, gas, and water supply	-2.270	-0.631	4.978	0.562	-0.040	0.081
2012–2013	S5	Construction	-0.548	-0.061	0.021	0.002	0.354	-0.018
2012–2013	S6	Wholesale and retail trade	6.105	0.306	1.318	0.057	-0.090	-0.030
2012–2013	S7	Hotels and restaurants	0.158	0.012	0.078	0.002	0.001	0.036
2012–2013	S8	Transportation and Storage	7.512	-0.428	0.631	0.037	0.214	-0.902
2012–2013	S9	Information and communication	0.115	-0.008	0.018	0.000	0.001	-0.003
2012–2013	S10	Financial intermediation	0.034	-0.010	0.001	0.001	0.001	-0.002
2012–2013	S11	Real estate activities	0.580	0.019	0.112	0.003	0.025	0.030
2012–2013	S12	Public administration and professional activities	0.217	0.000	0.003	-0.005	0.002	-0.000
2012–2013	S13	Education	0.002	0.001	0.019	0.026	0.000	0.001
2012–2013	S14	Health and social work activities	-0.021	0.002	0.031	0.039	0.000	0.004
2012–2013	S15	Other service activities	0.215	-0.004	0.007	0.003	0.003	-0.001

Table I.4: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2013–2014

Period	Sector_ID	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2013–2014	S1	Agriculture, hunting, forestry, and fishing	-0.170	-0.783	0.402	0.017	-0.512	0.208
2013–2014	S2	Mining and quarrying	3.205	0.283	0.274	0.018	-0.146	0.639
2013–2014	S3	Manufacturing	-1.561	-0.880	0.956	0.057	-0.034	1.276
2013–2014	S4	Electricity, gas, and water supply	0.372	-2.595	4.229	0.491	0.020	1.407
2013–2014	S5	Construction	-0.348	-0.010	0.014	0.002	0.300	-0.001
2013–2014	S6	Wholesale and retail trade	-1.414	0.093	1.523	0.057	-0.052	1.231
2013–2014	S7	Hotels and restaurants	-0.004	-0.003	0.081	0.003	0.001	0.058
2013–2014	S8	Transportation and Storage	2.784	-0.535	0.521	0.056	0.119	-0.049
2013–2014	S9	Information and communication	0.091	-0.014	0.006	0.000	0.001	0.000
2013–2014	S10	Financial intermediation	0.001	-0.012	0.005	0.000	0.001	0.002

2013–2014	S11	Real estate activities	0.446	0.003	0.083	0.003	0.023	0.036
2013–2014	S12	Public administration and professional activities	0.047	0.006	0.005	0.015	0.002	0.000
2013–2014	S13	Education	-0.056	0.001	0.019	0.020	0.000	0.001
2013–2014	S14	Health and social work activities	-0.006	0.005	0.020	0.020	0.000	0.001
2013–2014	S15	Other service activities	0.115	-0.012	0.039	0.003	0.002	0.003

Table I.5: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2014–2015

Period	Sector_ID	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2014–2015	S1	Agriculture, hunting, forestry, and fishing	-0.015	-1.190	-0.338	-0.004	0.669	-0.160
2014–2015	S2	Mining and quarrying	-0.372	-0.437	0.352	-0.004	0.533	-1.025
2014–2015	S3	Manufacturing	0.156	-0.734	1.002	-0.017	0.577	0.184
2014–2015	S4	Electricity, gas, and water supply	-11.066	3.348	7.610	-0.125	0.530	0.415
2014–2015	S5	Construction	-0.134	0.048	0.014	-0.001	0.083	0.013
2014–2015	S6	Wholesale and retail trade	-2.941	-0.400	1.295	-0.017	0.651	-0.139
2014–2015	S7	Hotels and restaurants	-0.269	-0.002	0.076	-0.001	0.002	0.009
2014–2015	S8	Transportation and Storage	0.724	-0.855	0.870	-0.035	0.237	-0.967
2014–2015	S9	Information and communication	0.130	-0.023	-0.003	-0.000	0.001	0.005
2014–2015	S10	Financial intermediation	0.017	-0.010	0.001	-0.000	0.002	-0.002
2014–2015	S11	Real estate activities	0.760	0.022	0.082	-0.001	0.025	0.002
2014–2015	S12	Public administration and professional activities	0.069	0.005	0.006	-0.019	0.001	-0.000
2014–2015	S13	Education	-0.051	0.001	0.022	0.000	0.000	0.001
2014–2015	S14	Health and social work activities	-0.059	0.004	0.030	-0.003	0.000	0.002
2014–2015	S15	Other service activities	-0.017	-0.016	0.006	-0.002	0.001	0.015

Table I.6: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2015–2016

Period	Sector_ID	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2015–2016	S1	Agriculture, hunting, forestry, and fishing	-0.231	-1.464	-0.048	0.001	0.679	0.068
2015–2016	S2	Mining and quarrying	-7.635	0.456	0.212	0.001	0.371	-0.527
2015–2016	S3	Manufacturing	-0.915	0.132	0.931	0.006	0.363	0.794
2015–2016	S4	Electricity, gas, and water supply	-7.759	1.409	5.127	0.036	0.754	0.555
2015–2016	S5	Construction	-0.063	0.079	0.018	0.001	0.037	0.000

2015–2016	S6	Wholesale and retail trade	-1.336	0.251	0.790	0.006	0.513	0.654
2015–2016	S7	Hotels and restaurants	0.117	0.000	0.061	0.001	0.001	0.021
2015–2016	S8	Transportation and Storage	-2.487	0.619	0.721	0.023	0.234	0.769
2015–2016	S9	Information and communication	-0.006	0.003	0.049	0.000	0.001	-0.005
2015–2016	S10	Financial intermediation	0.022	-0.002	0.007	-0.000	0.001	0.001
2015–2016	S11	Real estate activities	0.144	0.009	0.098	0.000	-0.007	0.016
2015–2016	S12	Public administration and professional activities	0.047	0.015	0.009	0.024	0.001	0.000
2015–2016	S13	Education	0.025	0.001	0.021	-0.003	0.000	0.000
2015–2016	S14	Health and social work activities	0.027	0.003	0.018	-0.006	0.000	0.000
2015–2016	S15	Other service activities	0.057	-0.002	0.048	0.001	-0.000	0.000

Table I.7: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2016–2017

Period	Sector_ID	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2016–2017	S1	Agriculture, hunting, forestry, and fishing	-0.020	-0.345	0.506	0.014	0.019	0.000
2016–2017	S2	Mining and quarrying	-7.711	-0.714	0.227	0.012	0.077	0.000
2016–2017	S3	Manufacturing	1.167	-1.030	1.009	0.052	0.195	0.000
2016–2017	S4	Electricity, gas, and water supply	15.319	-8.013	3.204	0.459	0.204	0.000
2016–2017	S5	Construction	0.055	0.022	0.018	0.004	0.118	0.000
2016–2017	S6	Wholesale and retail trade	-3.463	-0.799	1.010	0.054	0.106	0.000
2016–2017	S7	Hotels and restaurants	-0.212	-0.018	0.046	0.004	0.000	0.000
2016–2017	S8	Transportation and Storage	-2.523	-0.532	0.808	0.090	0.094	0.000
2016–2017	S9	Information and communication	-0.084	-0.008	0.041	0.001	0.000	0.000
2016–2017	S10	Financial intermediation	-0.033	-0.007	0.012	0.000	0.001	0.000
2016–2017	S11	Real estate activities	-0.310	-0.045	0.121	0.007	0.002	0.000
2016–2017	S12	Public administration and professional activities	-0.098	-0.006	0.005	0.052	-0.001	0.000
2016–2017	S13	Education	-0.049	-0.001	0.011	0.009	-0.000	0.000
2016–2017	S14	Health and social work activities	-0.040	-0.003	0.012	0.007	0.000	0.000
2016–2017	S15	Other service activities	-0.082	-0.025	0.047	0.005	-0.000	0.000

Table I.8: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2017–2018

Period	Sector	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2017–2018	S1	Agriculture, hunting, forestry, and fishing	-0.034	0.023	0.086	0.011	-0.182	1.066
2017–2018	S2	Mining and quarrying	-2.833	0.446	0.321	0.008	0.003	2.570
2017–2018	S3	Manufacturing	2.174	0.569	2.192	0.047	0.287	5.113
2017–2018	S4	Electricity, gas, and water supply	-6.870	-3.914	6.487	0.265	-0.056	5.101
2017–2018	S5	Construction	0.096	0.205	0.041	0.003	-0.082	0.028
2017–2018	S6	Wholesale and retail trade	-4.729	0.677	2.272	0.033	-0.307	3.826
2017–2018	S7	Hotels and restaurants	-0.315	0.007	0.085	0.002	-0.000	0.128
2017–2018	S8	Transportation and Storage	-2.872	0.664	1.283	0.061	-0.143	2.906
2017–2018	S9	Information and communication	-0.105	-0.001	0.054	0.000	-0.000	0.014
2017–2018	S10	Financial intermediation	-0.078	0.000	0.014	0.000	-0.001	0.010
2017–2018	S11	Real estate activities	-0.261	0.040	0.183	0.004	-0.022	0.179
2017–2018	S12	Public administration, and professional activities	-0.094	0.004	0.009	0.040	-0.001	0.003
2017–2018	S13	Education	-0.108	-0.000	0.016	0.002	-0.000	0.001
2017–2018	S14	Health and social work activities	-0.072	-0.000	0.015	0.000	-0.000	0.002
2017–2018	S15	Other service activities	-0.082	-0.013	0.064	0.003	-0.003	0.023

Table I.9: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2018–2019

Period	Sector	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2018–2019	S1	Agriculture, hunting, forestry, and fishing	-0.752	-0.001	0.811	0.006	-0.275	-0.126
2018–2019	S2	Mining and quarrying	0.434	0.146	0.191	0.004	-0.082	-0.574
2018–2019	S3	Manufacturing	-2.163	0.786	1.594	0.023	-0.216	-0.581
2018–2019	S4	Electricity, gas, and water supply	-5.332	-0.173	7.060	0.133	-0.481	-0.196
2018–2019	S5	Construction	-0.108	0.274	0.048	0.003	-0.230	-0.016
2018–2019	S6	Wholesale and retail trade	-0.918	1.460	1.734	0.019	-0.512	0.377
2018–2019	S7	Hotels and restaurants	0.045	0.006	0.082	0.001	-0.001	0.021
2018–2019	S8	Transportation and Storage	-0.234	0.825	1.142	0.042	-0.297	0.048
2018–2019	S9	Information and communication	0.009	-0.007	0.037	0.000	-0.001	0.002
2018–2019	S10	Financial intermediation	0.020	-0.000	0.011	0.000	-0.001	0.000
2018–2019	S11	Real estate activities	-0.005	0.040	0.164	0.003	-0.027	-0.008
2018–2019	S12	Public administration, and professional activities	0.088	0.003	0.010	0.032	-0.001	-0.000
2018–2019	S13	Education	0.029	-0.000	0.014	-0.001	-0.000	-0.000

2018–2019	S14	Health and social work activities	0.026	-0.001	0.015	-0.002	-0.000	-0.000
2018–2019	S15	Other service activities	0.040	-0.018	0.053	0.001	-0.003	0.007

Table I.10: Sectoral Contributions of SDA Effects to CO_2 Emission Changes, 2019–2020

Period	Sector	Sector Name	CO_2 Intensity Effect	Technology Effect	Household Effect	Government Effect	Investment Effect	Export Effect
2019–2020	S1	Agriculture, hunting, forestry, and fishing	-0.815	-1.182	1.959	0.006	-0.330	-0.685
2019–2020	S2	Mining and quarrying	9.213	-2.638	0.142	0.023	-0.274	-2.328
2019–2020	S3	Manufacturing	-1.952	-1.476	0.944	0.014	-1.304	-1.577
2019–2020	S4	Electricity, gas, and water supply	8.131	44.164	-31.369	0.246	-0.649	-4.476
2019–2020	S5	Construction	0.322	-0.853	-0.067	0.002	0.368	-0.033
2019–2020	S6	Wholesale and retail trade	-8.876	-0.740	-0.320	0.011	-0.173	-2.788
2019–2020	S7	Hotels and restaurants	-0.281	0.057	0.468	0.001	0.000	-0.638
2019–2020	S8	Transportation and Storage	-9.284	-2.638	1.773	0.007	0.022	-0.513
2019–2020	S9	Information and communication	-0.114	0.057	-0.064	0.001	0.001	-0.025
2019–2020	S10	Financial intermediation	-0.017	0.005	-0.017	0.000	0.001	-0.006
2019–2020	S11	Real estate activities	-0.550	-0.050	0.078	0.019	0.126	-0.365
2019–2020	S12	Public administration, and professional activities	-0.224	-0.124	-0.020	0.020	0.007	-0.002
2019–2020	S13	Education	0.014	-0.010	-0.039	0.008	-0.000	-0.012
2019–2020	S14	Health and social work activities	0.036	0.001	-0.056	-0.008	0.000	-0.017
2019–2020	S15	Other service activities	-0.257	0.255	-0.235	0.010	0.020	-0.062