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Structural Determinants of Carbon Market Effectiveness: A Machine Learning Approach to Emissions Trading Gaps in Developed and Developing Economies

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Abstract

Emissions Trading Systems (ETSs) have become some of the most widely adopted market-based instruments for reducing greenhouse gas emissions. However, their environmental performance varies considerably across jurisdictions, suggesting that carbon pricing mechanisms operate under heterogeneous structural and institutional conditions. This study analyzes the factors influencing CO₂ emissions performance in economies implementing ETSs. Grounded in Ecological Modernization Theory and Institutional Theory, the research combines a k-prototypes clustering model and an Artificial Neural Network (ANN). First, 58 ETSs across 53 countries were classified into four archetypes according to their institutional maturity, regulatory scope, and structural characteristics. Second, an ANN model was estimated using annual data from 2000–2021 to examine the influence of environmental, socio-demographic, economic, and development-related variables on CO₂ emissions per capita. The results show that ETS performance depends not only on economic development levels but also on broader structural and institutional factors. Renewable energy consumption and renewable energy production emerge as the most influential drivers of lower CO₂ emissions, particularly in developing economies. Conversely, urbanization, export-oriented activities, and governance weaknesses are associated with greater emissions pressures. Corruption also exhibits a stronger negative effect on environmental performance in emerging economies. Overall, the findings suggest that ETSs should not be viewed as standalone climate instruments; their effectiveness depends on complementary policies that promote renewable energy deployment, strengthen institutional quality, and address the pressures associated with trade and urbanization.

Keywords: Emissions Trading Systems; machine learning; greenhouse gases; developing economies; environmental policies



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1. Introduction

Over the past decade, instruments aimed at mitigating global warming have experienced substantial growth in their implementation worldwide, reflecting the global urgency of decarbonization. This momentum intensified following the adoption of the Paris Agreement in 2015, signed by 194 parties, which committed countries to strengthening

public policies and economic instruments to reduce Greenhouse Gas (GHG) emissions. The central objective of the Agreement is to limit the increase in global temperature to well below 2 °C above pre-industrial levels and, if possible, to 1.5 °C during this century (United Nations, 2026).

To achieve this goal and facilitate a green economy transition, each economy is expected to implement regulatory and market-based instruments consistent with its development capacities and structural conditions (United Nations, 2026). Among the primary market-based mechanisms adopted to control emissions are Emissions Trading Systems (ETSs). These instruments are designed to reduce GHG (carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), sulfur hexafluoride (SF₆), perfluorocarbons (PFCs), and hydrofluorocarbons (HFCs)) under the “cap-and-trade” principle. Under this framework, a maximum emission limit (cap) is established, and firms that do not use their full allocation of allowances may trade them in the carbon market.

It is important to note that an ETS establishes a maximum emissions cap and allows the trading of emission permits within a market, resulting in a variable carbon price. In contrast, a carbon tax sets a fixed price per ton of emissions without guaranteeing a specific level of emission reduction. In this way, the ETS provides greater market flexibility, while the carbon tax offers greater certainty regarding the cost of pollution (SEMARNAT, 2026). By placing a price on carbon, an ETS promotes decarbonization through quantitative constraints on emissions, particularly CO₂, one of the principal contributors to global warming. Although an ETS regulates multiple greenhouse gases, the present study focuses specifically on CO₂ emissions (European Commission, 2020).

Currently, 58 ETSs operate across 53 jurisdictions worldwide. The first large-scale system was implemented by the European Union in 2005, followed by New Zealand in 2008, sub-national programs in the United States of America (USA) in 2009, Japan in 2010, and, later, Canada, China, Kazakhstan, and South Korea in 2013. Since then, additional jurisdictions have adopted similar mechanisms. However, their geographical distribution remains uneven: approximately 74% of the ETSs operate in developed economies, while only 26% are implemented in developing markets. Kazakhstan was the first developing economy to adopt an ETS in 2013, followed by Mexico in 2020 and Malaysia and Montenegro in 2021; more recently, between 2023 and 2024, countries such as India, the Dominican Republic, Brazil, Argentina, Colombia, Chile, Indonesia, Thailand, Ukraine, Vietnam, the Philippines, and Turkey initiated similar frameworks (ICAP, 2026; IMF, 2015).

Despite the global diffusion of ETSs, post-implementation outcomes vary significantly across countries. Recent literature strongly synthesizes a prevailing consensus: the empirical outcomes and environmental effectiveness of carbon pricing are profoundly heterogeneous across different jurisdictions (Fredriksson & Svensson, 2003). These studies highlight that while emissions trading systems function optimally in highly regulated advanced economies, their implementation in developing economies often yields divergent results due to differing institutional constraints, informal economies, and varying paces of energy transition.

Evidence suggests a more favorable trend among developed economies. Considering the year each jurisdiction initiated its ETS, by 2024, all developed countries except China will have achieved reductions in carbon emissions. For example, the European Union has reduced emissions by 8.9%, the USA by 11%, New Zealand by 13.4%, Japan by 17%, Canada by 6.2%, South Korea by 8%, and the United Kingdom by 8.6%. In contrast, China has experienced a 23.6% increase in CO₂ emissions despite operating a national ETS. Developing economies exhibit a different pattern. Of the 16 developing jurisdictions that have implemented an ETS, only four have accumulated sufficient time series data to assess effectiveness: Mexico, Kazakhstan, Malaysia, and Montenegro. Since implementation,

Mexico has recorded a 7% increase in emissions, Kazakhstan 13%, and Malaysia 6%, while Montenegro is the only case demonstrating a modest reduction of 1%. These contrasting trajectories reveal a clear performance gap between developed and developing economies.

Based on the above, it can be observed that outcomes differ between developed and developing economies. This divergence suggests that there is no single determinant of ETS performance; rather, multiple variables beyond the mere reduction of carbon dioxide emissions shape their effectiveness, depending on each country's economic context. However, previous studies have largely overlooked this phenomenon. While much is known about carbon pricing in advanced economies, there is a theoretical and methodological gap in modeling the nonlinear, structural, and institutional frictions like corruption and reliance on external debt that dictate performance in developing economies using machine learning.

In developing economies, macroeconomic frictions such as external debt act as profound accelerators of environmental degradation. Recent literature establishes a direct mechanism: the pressure to service high external debt obligations heavily restricts the fiscal space necessary for green infrastructure and renewable energy investments. Consequently, developing nations are often forced to prioritize carbon-intensive, export-led economic growth to generate immediate foreign exchange and maintain debt solvency, effectively neutralizing decarbonization efforts (Zhao & Liu, 2022). Under these conditions, the “dirty growth” dilemma emerges, wherein governments implicitly subsidize heavy industries to prevent economic default, undermining the price signals that an ETS is supposed to generate.

Simultaneously, institutional quality, specifically the control of corruption, acts as a critical determinant of environmental policy success. While advanced economies benefit from strong regulatory frameworks that ensure the integrity of cap-and-trade systems, systemic corruption in developing markets severely distorts these mechanisms (Koengkan et al., 2021). Corruption sabotages market-based instruments through regulatory capture, fraudulent emissions reporting, and the misallocation of emission allowances, which artificially crash the carbon price and remove any incentive for corporate decarbonization (Mađziel & Campisi, 2022).

Thus, prevailing evidence dictates that without robust institutional oversight, the mere regulatory adoption of an ETS is structurally insufficient to curb CO₂ emissions in low-governance contexts. This dual interaction between high external debt and systemic corruption justifies their inclusion as critical explanatory variables in evaluating climate policy performance. In this regard, the primary objective of this study is to identify and model which structural, macroeconomic, and institutional variables most strongly influence CO₂ emissions in economies implementing ETSs. Ultimately, this aims to highlight which factors jurisdictions should prioritize based on their economic development to achieve better climate mitigation outcomes.

To further evaluate ETS performance, this research introduces a powerful machine-learning approach. First, it utilizes a clustering model via the k-prototypes algorithm to group the 58 existing ETSs according to their structural characteristics. Rather than relying solely on income-level categories, this data-driven approach identifies archetypes based on shared features, including institutional maturity, regulatory scope, and structural economic conditions. Secondly, this study proposes the construction of an artificial neural network (ANN) model, in which CO₂ emissions serve as the dependent variable across all economies implementing these mechanisms. The model incorporates a comprehensive set of explanatory variables classified into environmental, economic, and social dimensions. These variables include both structural factors common to all economies and characteristics that tend to be more pronounced in developing countries, such as fossil fuel dependency, governance weaknesses, inflationary pressures, and institutional fragility. This machine

learning approach deliberately overcomes the limitations of traditional linear econometric panel data tests by allowing for a non-linear, multivariate framework capable of identifying the determinants that most significantly influence CO₂ trajectories and determining whether deeply embedded structural conditions in lower-income economies constrain the environmental effectiveness of ETSs.

Ultimately, this approach aims to advance a more rigorous understanding of climate policy performance and to provide evidence-based recommendations for improving the design, reform, and applicability of environmental public policies across diverse development contexts. Explicitly, this study advances the field through six distinct contributions: 1. Advancing environmental economic theory by modeling non-linearities and structural frictions between emissions and country-specific characteristics. 2. Methodological innovation via the k-prototypes algorithm for data-driven policy archotyping rather than simple income grouping. 3. Empirical expansion by compiling and analyzing performance data across 53 jurisdictions. 4. Practical frameworks for institutional governance to improve climate policy effectiveness. 5. Integration of macroeconomic debt and credit variables with carbon outcomes. 6. Strategic implications for international green finance flows to assist developing markets in their transition.

The remainder of this article is organized as follows: Section 2 presents the literature review, covering the conceptual foundations of Emissions Trading Systems, their environmental and economic performance, their role in CO₂ mitigation, their relationship with the Sustainable Development Goals, approaches to measuring ETS performance, differences between developed and developing economies, and the theoretical framework underpinning the study. Section 3 describes the data sources, variable selection process, and methodological approach, including the k-prototypes clustering model and the ANN used to analyze CO₂ emissions performance. Section 4 presents the empirical results, including the identification of ETS archetypes and the sensitivity analysis of the ANN model. Section 5 discusses the main findings in relation to the existing literature and highlights their theoretical and practical implications and presents the policy implications derived from the results. Finally, Section 6 summarizes the main findings and contributions, discusses the study's limitations, and outlines directions for future research.

2. Literature Review

2.1. Emissions Trading Systems as Environmental Policy Instruments and Their Conceptual Foundations

In recent years, ETSs have been used as well-established and fundamental instruments for the design and evaluation of market-based environmental policies, with the aim of mitigating greenhouse gas emissions (Kaplan, 2026). Importantly, ETSs operate under a framework in which, to reduce industrial impacts in terms of emissions, authorities set a cap on the amount of emissions that industries are allowed to generate and allocate this cap through tradable permits. This allows organizations that operate below their allocation, i.e., those with surplus allowances, to sell them, while those with higher emissions must purchase allowances to remain within the permitted limit (Friedlingstein et al., 2025).

It is important to note that the concept of climate change-related emissions is commonly expressed in terms of greenhouse gases such as carbon dioxide, methane, nitrous oxide, and hydrofluorocarbons. However, carbon dioxide is typically treated as the reference gas due to its predominance in emissions from trade and industry and, consequently, because fossil-fuel combustion is one of the most readily measurable sources (Hodnebrog et al., 2020). Therefore, assessing ETS performance using carbon dioxide as the reference measurement variable becomes essential, as it enables a more homogeneous comparison across economies regardless of specific methodological design features (Kaplan, 2026).

The literature often frames the ETS as a logical process in which “rights” over emissions generated by industries are allocated or defined (Dechezleprêtre et al., 2023). In other words, it involves a clarification of rights that simultaneously enables trading, which can lead to a more efficient allocation of emissions by creating benefits for industries that prioritize optimization over excessive production (Friedlingstein et al., 2025). These foundations underlying ETS implementation are also commonly linked to the social welfare needs of contemporary communities.

ETSs, as climate policy instruments, must be understood within the broader framework of anthropogenic climate change. This is because the main concern lies in the sustained accumulation of greenhouse gases derived from human activities, rather than in the existence of natural CO₂ fluxes (Keller et al., 2018). CO₂ is indeed part of natural cycles through the oceans, vegetation, and soils; however, the main problem currently identified arises primarily from the imbalance generated by human activity. From this perspective, ETSs become relevant as instruments designed to regulate anthropogenic emissions rather than those generated naturally.

From this standpoint, it becomes evident that the evolution of international climate governance, particularly since the Kyoto Protocol (Maamoun, 2019), represents an important point of reference, as it was strongly linked to emission reduction commitments for industrialized economies and introduced market-based mechanisms, including emissions trading. This relationship can therefore be understood as a key antecedent of what would later become the global carbon market and ETSs worldwide.

Now, over the past two decades, ETSs have diversified and expanded their scope (J. Tang et al., 2018). This expansion has led to differences in sectoral coverage, levels of stringency, allocation rules, monitoring capacities, and other design features. As a result, a broad range of research streams has emerged on the performance of ETS implementation across contexts, enabling comparisons of policy design and execution (Borghesi et al., 2023; Martin et al., 2016). Therefore, analyzing ETS performance in implementing countries becomes essential to identify areas for improvement and to develop strategies to strengthen the instrument.

2.2. ETS Performance: A Multidimensional Approach

Given the characteristics of an ETS, the literature consistently concludes that its performance cannot be measured in a one-dimensional manner (Martin et al., 2016). Even in reviews that focus on a single country as the unit of analysis, evidence is often developed that supports framing the ETS as a multidimensional object of assessment (R. Tang et al., 2018; Vlachou, 2014). Accordingly, it has become essential to structure ETS performance evaluation across at least two dimensions, environmental and economic, which, in turn, also makes it possible to assess innovation and technological performance as well as market functioning (Koch et al., 2014), while always taking into account the social context of the country in which the analysis is conducted (Balogh & Mizik, 2021).

As a consequence of the environmental and economic effects derived from ETSs, the literature points to an opportunity gap for understanding how improvements in environmental and economic performance may translate into an innovation and technology dimension (Calel & Dechezleprêtre, 2016). That is, if implemented regulations can be reflected in measurable evidence of carbon dioxide reductions and in justifiable economic outcomes, it becomes possible to identify adjustment mechanisms related to clean technologies and innovative decarbonization processes (Calel & Dechezleprêtre, 2016; Martin et al., 2016). This could enable the development of targeted strategies focused on cleaner production models (Khabbazan & Hokamp, 2022).

Thus, recent literature reinforces the idea that ETS performance should be understood in connection with the energy transition and the restructuring of national production systems (Y. Tang et al., 2025). From this perspective, putting a price on carbon implies imposing quantitative restrictions on emissions while also generating incentives for cleaner energy use, promoting technological modernization, and forcing changes in local government behavior. In this sense, evidence from China shows that implementing an ETS can significantly accelerate the energy transition through strategies such as modifying incentives, establishing specific and clear constraints, and taking into account factors oriented toward green innovation.

On the other hand, European evidence suggests that decarbonization policies continue to generate heterogeneous environmental and economic effects across countries. Torok (2023) points out that several European Union member states have achieved a decoupling, although limited, between economic growth and environmental pressure. In other cases, however, emissions reductions have coincided with lower levels of economic performance, making this a factor that deserves particular attention. Along the same lines, Simionescu (2025) shows that, despite the decoupling observed in several European Union countries between emissions and growth, carbon-intensive energy consumption patterns persist, which highlights a clear need for technological changes that complement public policies.

Complementary evidence also suggests that the effects generated by public decarbonization policies should be interpreted within a broad framework of sustainability and governance. From this perspective, Bagadeem (2025) argues that macroeconomic conditions and sustainability practices jointly influence carbon emissions performance at the firm level, emphasizing that environmental outcomes therefore depend on more factors than a single regulatory instrument alone. This perspective provides a clear framework for understanding ETSs and their study, as it supports the idea that carbon markets may be more effective when they are developed and implemented alongside institutional and governance mechanisms and with a sustainability-oriented approach that strengthens environmental performance.

The topic of ETSs in the literature is primarily associated with the reforms implemented throughout the different phases of the European Union Emissions Trading System (EU ETS) (Friedrich et al., 2020). Although the EU ETS is considered one of the most important and internationally recognized carbon markets, as well as one of the most mature systems, several studies have highlighted that its initial phases faced significant challenges, particularly related to the over-allocation of allowances, low carbon prices, and a limited capacity to incentivize substantial emissions reductions (Dueñas & Mandel, 2025). These shortcomings created the need for prompt corrective actions. Consequently, subsequent reforms introduced more robust allocation mechanisms, a gradual reduction in subsidies, and market stability instruments aimed at improving the effectiveness of the system.

Continuing this line of thought, the literature presents divergent views regarding the effectiveness of these reforms. While some authors argue that the implementation of new reforms within the EU ETS has strengthened carbon pricing mechanisms and enhanced decarbonization capacity, others contend that challenges related to market volatility, speculation, and regional heterogeneity continue to affect both environmental and economic outcomes (Salvagnin, 2024). These contrasting findings suggest that the performance of an ETS depends not only on the instrument itself, but also on its institutional capacity, regulatory design, and the economic context in which it operates.

2.3. Functioning of ETS and Their Role in CO₂ Reduction

An ETS is a market-based environmental policy instrument designed to limit GHG emissions in specific sectors of the economy. Its primary objective is to progressively

reduce these emissions, thereby contributing to global warming mitigation. While carbon dioxide (CO₂) remains the most strictly regulated gas due to its volume, these schemes are increasingly designed to include other potent pollutants such as methane (CH₄), nitrous oxide (N₂O), sulfur hexafluoride (SF₆), perfluorocarbons (PFCs), and hydrofluorocarbons (HFCs). The functioning of an ETS is based on the allocation of emission allowances or permits to regulated firms, which can be traded within a carbon market. The scope of the system depends on the design of each country's environmental policy and may cover sectors such as manufacturing, mining, energy generation, or other emission-intensive industries. The emissions cap is determined according to the productive structure of the economy and the climate targets established by the government.

In practice, environmental authorities assign an annual emissions limit to each firm. If a company seeks to increase production, rather than proportionally increasing its emissions, it is incentivized to invest in clean technologies, energy efficiency, and sustainable processes that allow it to expand output without exceeding its allocated limit. In cases where the firm surpasses its emissions cap, it must incur a cost for each additional ton emitted, with the price determined either by regulatory mechanisms or market dynamics. In more advanced systems, emission allowances can be traded among firms within a carbon market. Companies that reduce their emissions below their allocated levels can sell their surplus permits, while those facing greater challenges in reducing emissions may purchase additional allowances. This mechanism generates economic incentives for technological innovation and the adoption of sustainable practices.

In the specific case of China, recent literature has devoted considerable attention to the performance of its national carbon market, primarily because it represents the world's largest ETS in terms of covered emissions (Ge et al., 2024). Although several studies agree that the Chinese carbon market has contributed significantly to reductions in carbon intensity and, more importantly, to increased regulatory oversight of industrial emissions, important structural challenges have also been identified. Among the main challenges are low carbon prices, limited sectoral coverage, regional disparities in institutional capacities, and strong government intervention, which contrasts with more mature systems such as the European ETS (Wang et al., 2025).

Furthermore, several authors argue that the Chinese system is still undergoing development and remains in a transitional stage, evolving from a regional pilot scheme toward a more consolidated national market. As a result, its environmental and economic effects continue to produce heterogeneous and sometimes ambiguous outcomes. This type of discussion is particularly relevant for developing economies, as it demonstrates that the implementation of an ETS requires gradual processes of institutional learning and governance development, particularly in terms of regulatory strengthening (Dong et al., 2016).

In the long term, an ETS promotes the transition toward a low-carbon economy by encouraging investment in clean technologies, reducing the carbon intensity of production, and ultimately contributing to the reduction of emissions at both national and global levels. In this sense, an ETS has become a key instrument for advancing more sustainable industrial systems.

2.4. The SDGs as a Framework for Emissions Mitigation

From an international perspective, the effort to reduce emissions has given rise to a range of environmental debates. These debates stem from the multilateral commitments that have developed around climate policies and the development agendas being implemented. Therefore, goals such as SDG 7, Affordable and Clean Energy, and SDG 13, Climate Action, become key references for the implementation of public policies that support their achievement (United Nations, 2015). Within this framework, and from a perspective fo-

cused on mitigating the impact of greenhouse effects, the aim is to reduce the footprint generated by industrial activities that are necessary to ensure social and economic progress without compromising natural capital (Janetschek et al., 2020).

Thus, through instruments such as the SDGs, commitments are generated in relation to operational mechanisms in which, through clearly defined targets and specific public policies, the mitigation of environmental impact risks is pursued (Iacobuță et al., 2022). This encourages the adoption of various market-based regulatory instruments, which become a means of advancing toward the fulfillment of broader priorities such as the 2030 Agenda. In conclusion, there is a clear need to establish specific targets for deep, rapid, and sustainable emissions reductions in support of mitigation efforts, and the achievement of goals such as SDG 7 and SDG 13 represents a relevant starting point for their development (Janetschek et al., 2020).

The SDGs are not only intended to serve as an international normative framework, but also as an operational reference that makes it possible to analyze the reduction of emissions intensity and the gap between economic growth and environmental pressure. From this perspective, recent literature suggests that progress toward more sustainable development requires not only reducing absolute emissions, but also strengthening decoupling processes consistent with the energy transition and long-term environmental goals. Gbadeyan et al. (2024) argue that strategies focused on clean and sustainable technologies contribute to the achievement of environmental objectives by promoting production patterns that are less carbon-intensive.

Complementing this idea, Basu and Ishihara (2025) expand the discussion by noting that the Environmental Kuznets Curve, which describes a relationship between economic development and environmental degradation, should be interpreted with caution, since decoupling does not occur automatically as a result of economic growth, but rather from the interaction between technological transformations, energy structure, and the quality of public policies. Thus, the SDGs can be understood as a guide for evaluating the extent to which economies are advancing toward forms of development that are compatible with decarbonization.

2.5. Measuring Carbon Dioxide Performance

2.5.1. Environmental

It is important to clarify what environmental performance means in the ETS context: namely, the ETS's ability to reduce carbon dioxide emissions, lower carbon intensity, or promote the more efficient use of carbon in relation to energy use within the covered sectors (Kaplan, 2026). However, the literature shows that indirect mechanisms may also shape the ETS's effectiveness, for example, through changes in production structure or technology substitution, which should be considered when reporting and interpreting results (Calel & Dechezleprêtre, 2016; Martin et al., 2016). Considering carbon markets, evaluations have shown specific patterns, such as dependence on the quality of monitoring, reporting, and verification (MRV); the consistency of the implemented rules; and the credibility of the resulting evidence.

A key challenge when comparing developed and developing economies is distinguishing observed outcomes from those that are truly attributable to the ETS, since carbon dioxide reductions may also be driven by factors such as carbon prices, industrial cycles, and complementary policies (Perino & Willner, 2016). With this in mind, the literature suggests using a robust evaluation approach that combines emissions indicators with multiple contextual variables to improve the accuracy of calculations and interpretations regarding ETS performance (Dechezleprêtre et al., 2023).

The evaluation of ETS performance must take into consideration the incidence of exogenous factors that may modify the level of emissions and, therefore, market outcomes independently of the formal instrument itself. Among the most relevant factors are fluctuations in economic activity, energy prices, regulatory uncertainty, and other external conditions that alter production behavior, energy demand, and the carbon price (Koch et al., 2014).

The literature has shown that an important part of the dynamics observed in emissions markets does not respond solely to the ETS itself, but also to macroeconomic and energy-related conditions that may amplify, weaken, or distort both its effectiveness and the interpretation of its implementation (Kanamura, 2016). Therefore, emissions reductions should not be attributed exclusively to the ETS mechanism, particularly because performance assessments do not always adequately control for the external conditions under which each system operates.

2.5.2. Economic

The economic performance dimension is also relevant when assessing ETS outcomes, as it can influence production, employment, competitiveness, and economic growth (Martin et al., 2016). Although impacts are often measured from a broad, aggregate perspective, it is also possible to consider how an ETS supports productivity gains or facilitates a transition toward sectors that reduce carbon use (Srivastav et al., 2018). Empirical evidence, however, shows mixed results regarding the economic effects of carbon regulation: in some cases, negative effects are reported and linked to compliance costs or sector-specific constraints, while in other cases, neutral effects are observed (Borghesi et al., 2023), particularly when the ETS is accompanied by innovation-oriented measures or more dynamic markets.

Building on this idea, a key finding for interpreting gaps in economic performance is market vitality. That is, factors such as low carbon prices, limited coverage, or insufficient participation can signal weak effects of the implemented measures—both economically and environmentally (Perino & Willner, 2016). At this point, it is also important to note that although ETSs do not explicitly differentiate across countries beyond the levels of pollution they regulate, clear differences can still be observed between developed and developing economies in terms of economic outcomes and the effects these measures generate (Balogh & Mizik, 2021).

2.6. Developed Economies vs. Developing Economies

Comparing ETSs across developed and developing economies requires recognizing that performance differences are not one-dimensional—that is, they do not stem solely from policy arrangements, but also from institutional, productive, and trade contexts (R. Tang et al., 2018). In this regard, ETSs in developed economies often operate within more stable regulatory frameworks and with more consolidated implementation capacities, whereas in developing economies, the adoption of such measures tends to be gradual, with frequent adjustments and institutional constraints (Srivastav et al., 2018). Therefore, the literature highlights a gap in how decarbonization measures are implemented in developed countries versus developing countries, which can affect how the effects of these measures are assessed.

Current literature also indicates that climate policy and trade generate diverse impacts and strategies. In developing countries, these issues have most often been examined through qualitative approaches, and it is noted that quantitative studies generally do not adequately incorporate the role of these countries within globalized value chains given their specific contexts—creating limitations when measuring impacts (Borghesi et al., 2023; R. Tang et al., 2018). This observation is crucial for properly studying ETS impacts because,

if structural factors are not controlled for, there is a risk of conflating an ETS-design gap with a development-conditions gap (Dechezleprêtre et al., 2023).

Accordingly, the literature suggests that a performance gap exists between developed and developing economies due to context-specific conditions that must be taken into account (Kaplan, 2026). Within this framework, an ETS may show carbon dioxide reductions without clearly differentiating by context, which can lead to ambiguous measurements and, consequently, to policies that are not well aligned with the needs of the economy in which they are implemented. For this reason, there is a clear need to evaluate metrics capable of capturing the heterogeneous nature of ETS functioning and outcomes.

Recent evidence also suggests that the relationship between economic development and environmental degradation is not linear and differs substantially between developed and developing economies. Using quantile regression techniques, Ganda and Ruza (2025) demonstrate that the effects of development-related factors on environmental performance vary according to emission levels and the structural characteristics of each country. These findings reinforce the need to evaluate ETS performance within differentiated development contexts rather than assuming homogeneous environmental responses across economies.

Theoretical Framework

To contextualize the mechanisms driving CO₂ mitigation within Emissions Trading Systems (ETSs), this study is anchored in a complementary framework integrating Ecological Modernization Theory (EMT) and Institutional Theory. EMT posits that continued economic development can decouple from environmental degradation through structural transitions, technological innovation, and market-based mechanisms like carbon pricing (Mol et al., 2020; York & Rosa, 2003). While this framework justifies the inclusion of macroeconomic and structural variables in our analysis, EMT's core assumptions are deeply rooted in the historical context of advanced economies. Consequently, it often conflicts with the empirical realities of developing markets, which frequently face competing priorities between rapid industrial growth for poverty alleviation and environmental reform.

To harmonize this discrepancy, Institutional Theory provides a critical bridge. It asserts that market mechanisms do not operate in a vacuum; rather, their efficacy is fundamentally bound by the quality of the underlying governance structures (North, 1990). In developing and transitioning economies, pervasive “institutional voids” such as inconsistent regulatory enforcement, lack of administrative capacity, or weak rule of law can render otherwise well-designed ETS policies ineffective (Acemoglu et al., 2005; Kostova et al., 2008).

By synthesizing these perspectives, this study acknowledges that while EMT outlines the macroeconomic pathways for decarbonization, Institutional Theory dictates the regulatory capacity required to actually achieve it. This dual theoretical lens directly supports our core premise: the specific structural and institutional variables jurisdictions must prioritize to optimize ETS outcomes are inherently dictated by their current stage of economic development.

2.7. Determinants of Performance and Analytical Approaches in ETS

From the perspective of economic theory, ETS performance is understood in terms of its ability to achieve emissions reductions while doing so at the lowest possible social cost. For this to occur, however, there must be a clear and functional price signal, and participating agents must respond to it—making the instrument's efficiency observable in practice (Stavins, 2011). Yet, this efficiency often remains largely theoretical because it is conditioned by factors such as the capacity and quality of monitoring, reporting, and verification (MRV) systems and, more broadly, by the institutional ability to document and communicate progress (Kaplan, 2026).

Regulatory credibility is another key factor in the economic logic of an ETS, as it directly shapes investment decisions and organizational commitments to adopt sustainable mitigation strategies (Borghesi et al., 2023). Consequently, the literature repeatedly emphasizes that variables such as compliance, credibility, and institutional capacity should be treated as fundamental determinants of ETS performance (Martin et al., 2016). Beyond clarifying core measurement issues, incorporating these determinants helps to better operationalize the economic theory underlying the instrument.

Another aspect to consider when assessing an ETS is recognizing its limited suitability as a homogeneous policy instrument. In practice, ETS architectures can differ substantially in regulatory features such as sectoral scope, allocation rules, and market-stability mechanisms (Borghesi et al., 2023). Such differences can generate distinct scenarios that may not be desirable from a regulatory standpoint. Therefore, an ETS may produce variations in the price signal, market liquidity, and the intensity of incentives to reduce emissions, inevitably leading to divergent performance outcomes even when instruments are labeled similarly.

An important debate within the ETS literature concerns the limitations of Monitoring, Reporting, and Verification (MRV) systems, particularly in developing economies (Dai & Pollitt, 2025). In this regard, the evidence emphasizes that the effectiveness of an ETS depends largely on institutional quality and the capacity of governments to monitor emissions in an efficient, consistent, and verifiable manner. From this perspective, several developing economies face challenges in their MRV systems related to data availability, shortages of specialized personnel, and the absence of standardized methodologies across productive sectors.

Continuing this line of thought, the limitations faced by developing economies may undermine the credibility of carbon markets, reducing participants' confidence and creating challenges in the allocation and oversight of emissions allowances (Zhang et al., 2018). As a result, several studies argue that strengthening institutional capacities and improving mechanisms for monitoring, reporting, and verifying the implementation of these systems are essential prerequisites for enhancing the environmental performance of ETSs in these economies.

The rapid growth of climate, energy, and industrial data has enabled the adoption of new tools for environmental analysis. One such tool is machine learning, which supports the study of carbon markets, environmental policies, and forecasting tasks (Hao & Tian, 2020). In the ETS context specifically, machine learning is often used to forecast carbon prices or model volatility by identifying variables that explain market dynamics, thereby producing more precise estimates (Friedlingstein et al., 2025). In addition, machine learning has also been used as an integrative approach for combining multiple indicators into clearer parameters of measurement and performance, which becomes especially valuable for deeper and more accurate analyses.

It is important to emphasize that, for the purposes of this study, the concept of a performance gap refers to the differences in environmental performance observed between developed and developing economies that have implemented ETSs. Environmental performance is defined as the level of CO₂ emissions per capita, which constitutes the dependent variable in the empirical analysis. Accordingly, lower levels of CO₂ emissions per capita are interpreted as better environmental performance. Therefore, the performance gap reflects the extent to which structural, environmental, socio-demographic, economic, and development-related factors contribute to differences in CO₂ emission outcomes across economies operating under ETS frameworks.

3. Methods and Data

We started this research with data collection, including ETS characteristics and country-level variables, followed by data preprocessing steps such as cleaning, scaling, handling missing values, and variable selection. The analysis then branches into two complementary components: a clustering analysis using the k -prototypes algorithm, in which the number of clusters is determined using the elbow method and the maximum curvature criterion, and an ANN model optimized with the Adam algorithm and trained with mean squared error loss. Then, we apply the ANN model to conduct a sensitivity analysis, in which selected variables are systematically varied ($\pm 5\%$, $\pm 15\%$, $\pm 30\%$) to evaluate their influence on emission outcomes. Finally, the results characterize ETS archetypes and their performance, leading to conclusions and policy implications. Figure 1 illustrates the analytical workflow of the study.

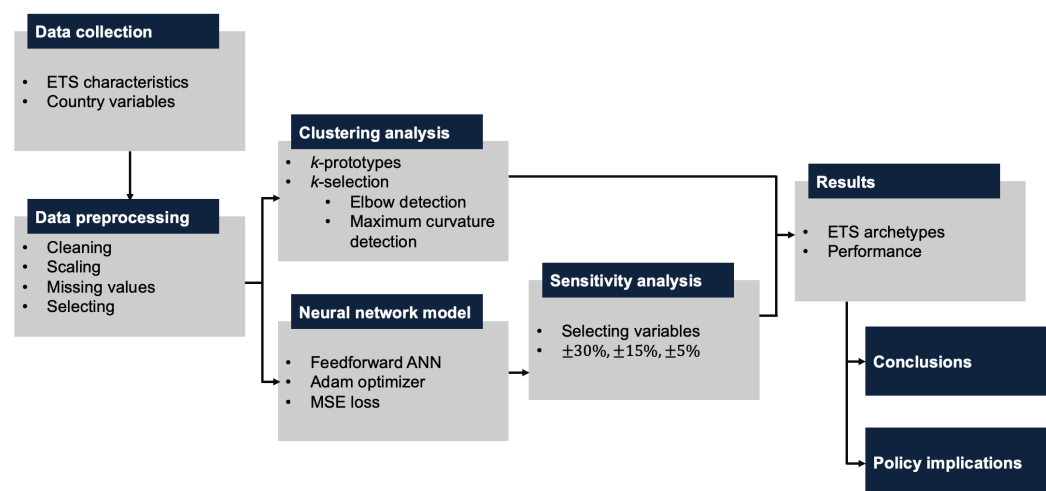


Figure 1. Analytical framework of the study.

The empirical analysis of this study is based on international databases. For the clustering stage, information on the status and design of the 58 ETSs was obtained from the International Carbon Action Partnership (ICAP) reports and ICAP ETS Map, which provide comparable information on the status of each system, the regulated gases, sectoral coverage, monitoring mechanisms, sanctions, and years of operation across different jurisdictions. In turn, to develop the performance gap model, an annual country-level database was constructed for the period analyzed (2000–2021), mainly using indicators obtained from the World Development Indicators of the World Bank. In addition, the information was complemented with CO₂ emissions per capita data from Our World in Data and corruption data from the Corruption Perceptions Index of Transparency International.

Additionally, the classification of countries into developed and developing economies was based on the country group scheme of the World Economic Outlook of the International Monetary Fund. Taken together, these information sources were intended to strengthen the comparability, transparency, and reproducibility of the study by explicitly identifying the origin of both the institutional ETS variables used and the macro-structural indicators employed in the neural network model and its analysis.

3.1. Data Description

We used two data sets as the basis for this research project. The first one was used as an input to form clusters, and the second was used for modeling the performance gap.

3.1.1. Data for Clustering ETSs

We considered 15 variables capturing three core dimensions of ETS design: institutional maturity, regulatory scope, and structural characteristics. For the first dimension, the variables we examine include: the status of the system (whether it is under consideration, under development, or in force); the existence of monitoring systems; and the penalty for exceeding emissions per tonne per year (classified as penalty, no penalty, or in draft). The variables for the second aspect include: the presence of a GHG emission limit; whether the ETS considers only CO₂ emissions or includes other gases; and binary indicators showing sectoral coverage across diverse sectors: energy, agriculture, industrial processes, waste, mining, transportation, buildings, and maritime. Finally, regarding structural features, we look at the average GHG target and the average duration of operation.

The variables collected for the design of the ETS were obtained from the ICAP ETS Map and cross-checked against the most recent ICAP reports. This was done to ensure consistency in the classification of the degree of regulatory scope, maturity, and the operational characteristics of each system.

Table 1 summarizes the descriptive statistics of the 15 variables used in the ETS clustering analysis. In particular, Table 1 presents the mean, standard deviation (Std. Dev.), the minimum (Min), and maximum (Max) values for each variable. Note that for the first variable, the status of the system, we consider three dummy variables: in consideration, in development, and in force. Most systems exhibit relatively high institutional maturity, with the majority already in force and characterized by monitoring and penalty mechanisms. Regulatory coverage varies considerably across sectors, being more extensive in energy and industrial processes and more limited in buildings, transport, and maritime activities. Structural characteristics show substantial dispersion, particularly in emissions targets, reflecting heterogeneous levels of ambition and maturity across ETSs.

Table 1. Descriptive statistics of the variables used in the ETS clustering.

Variable	Mean	Std. Dev.	Min	Max
Institutional Maturity (%)				
In consideration	0.17	0.38	0.00	1.00
In development	0.17	0.38	0.00	1.00
In force	0.66	0.48	0.00	1.00
Monitoring system	0.84	0.37	0.00	1.00
Penalty in place	0.59	0.50	0.00	1.00
Regulatory Scope (%)				
Emission limits	0.60	0.49	0.00	1.00
Multi-gas coverage	0.47	0.50	0.00	1.00
Energy	0.78	0.42	0.00	1.00
Agriculture	0.38	0.49	0.00	1.00
Industrial Processes	0.88	0.33	0.00	1.00
Waste	0.38	0.49	0.00	1.00
Mining	0.31	0.47	0.00	1.00
Transport	0.34	0.48	0.00	1.00
Building	0.26	0.44	0.00	1.00
Maritime	0.12	0.33	0.00	1.00
Structural Characteristics				
Average GHG target	691.43	1961.41	3.50	14,314.00
Average years of operation	6.57	5.64	1.00	21.00

3.1.2. Data for Modeling the Performance Gap

The methodological approach adopted in this study uses an ANN model to analyze the behavior of CO₂ emissions across countries that have implemented ETSs over time. The objective of this model is to capture complex, non-linear relationships between carbon emissions and a set of explanatory variables that may influence environmental performance under ETS frameworks. To construct the model, a dataset comprising 53 countries that host 58 ETSs worldwide was compiled. All European Union member states participating in the EU ETS were included as individual observations. The data were collected for the period spanning from 2000 to 2021, allowing for a longitudinal assessment of emissions trajectories before and after ETS implementation.

Countries were categorized according to their level of economic development, distinguishing between developed and developing economies. The developed group includes Australia, Canada, China, the USA, Japan, South Korea, New Zealand, Taiwan, the United Kingdom, Switzerland, and the European Union. The developing group comprises Argentina, Brazil, Chile, Colombia, the Dominican Republic, India, Indonesia, Kazakhstan, Malaysia, Mexico, Montenegro, the Philippines, Thailand, Turkey, Ukraine, and Vietnam.

The model incorporates a total of 22 variables. CO₂ emissions per capita serve as the dependent variable, while the independent variables are grouped into four analytical dimensions. The first dimension, Environmental Variables, includes indicators that provide an overview of each country's environmental profile, capturing aspects related to energy structure, renewable energy adoption, and overall environmental practices. The second dimension, Socio-Demographic Variables, comprises population-related indicators that reflect demographic scale and urbanization dynamics, offering insight into population size, density, and urban growth patterns. These factors help contextualize the structural pressures associated with emissions. The third dimension, Economic Variables, encompasses indicators linked to macroeconomic performance and productive structure, such as output levels, trade integration, and investment flows. These variables characterize the broader economic environment in which climate policies operate and influence emission trajectories. Finally, the fourth dimension, Development-Level Variables, includes structural indicators specifically selected to capture characteristics that tend to be more pronounced in developing and developing economies.

The classification of variables into four dimensions responds to the inherently multidimensional nature of ETS performance. First, environmental variables capture the energy structure, which constitutes a direct determinant of CO₂ emissions, as carbon intensity depends on the type of energy sources utilized (Apergis & Payne, 2010; Shafiei & Salim, 2014; Stern, 2004). Second, socio-demographic variables incorporate structural pressures associated with population dynamics and urbanization, which have been widely identified as key drivers of emissions growth due to increased energy demand and economic activity (Musse et al., 2026). In turn, economic variables reflect the macroeconomic environment and productive structure, as economic growth, international trade, and investment directly influence emission levels, consistent with the empirical evidence derived from the Environmental Kuznets Curve hypothesis (Dinda, 2004; Shahbaz et al., 2013). Finally, development-level variables capture institutional and structural factors that differentiate developing from developed economies, such as governance quality and institutional stability. These elements play a crucial role in shaping the effectiveness of environmental policies and the capacity for regulatory compliance (Fredriksson & Svensson, 2003; Welsch, 2004).

The variables selected in this study were chosen based on their influence on the behavior of carbon emissions. For instance, Song et al. (2026) finds that electricity consumption is one of the main sources of CO₂ emissions, with emission levels depending on the type of energy used: fossil fuel-based energy increases emissions, whereas renewable energy

sources significantly reduce them. Similarly, energy production from fossil fuels remains the primary source of carbon emissions, particularly within the energy sector, which accounts for more than 75% of total GHG emissions. As the use of fossil-based energy increases, so do the levels of CO₂ released into the atmosphere (Ahuja et al., 2025). In contrast, the use of renewable energy contributes to the reduction of CO₂ emissions, confirming its role as a key driver of decarbonization (Volodzquienė & Streimikiene, 2026).

From a socio-demographic perspective, the growth of the urban population contributes to higher CO₂ emissions by intensifying energy demand and reinforcing reliance on fossil fuels, particularly in contexts with limited renewable energy infrastructure (Musse et al., 2026). At the same time, economic factors such as economic growth, foreign direct investment, and international trade influence CO₂ emissions by reshaping economies' energy and production structures. While these factors may generate partial reductions, they do not eliminate emissions due to the persistent dependence on fossil fuels (Duc & Lai, 2026).

Furthermore, carbon policies contribute to emission reductions but generate differentiated effects on inflation, which may either increase or decrease depending on whether adjustments occur in the short term or through expectations related to the energy transition (Degaspero et al., 2026). Population migration also plays a significant role, as it increases CO₂ emissions by raising transport demand and accelerating urbanization, although its effects vary according to the level of development and technological capacity of regions (Li & Li, 2025). In the same vein, corruption is associated with higher CO₂ emissions by weakening the implementation and enforcement of environmental policies, with a more pronounced effect observed in contexts of illegal corruption (Montes & Landim, 2026). Similarly, external debt, together with CO₂ emissions, acts as a constraint on sustainable development by limiting the capacity of economies to invest in environmental policies and energy transitions (Musse et al., 2026).

Table 2 details each variable included in the analysis, specifying its corresponding dimension and unit of measurement. The first 21 variables constitute the independent variables set, and the last one (CO₂pc) depends on this set.

Table 2. Variable operationalization framework for the ANN model.

Variable	Definition	Unit Adopted	Source
Institutional and Temporal Variables			
Year	Calendar year of observation, ranging from 2000 to 2021.	Years	Not Applicable
# ETS	Number of ETSs present within a country in a given year.	Count	International Carbon Action Partnership (2024)
EUmember	Binary indicator equal to 1 if the country is a member of the European Union and 0 otherwise.	(0/1)	International Carbon Action Partnership (2024)
Environmental Variables			
EnergyCon_pc	Electric power consumption per capita, measured as total electricity generated by power plants and combined heat and power plants, minus transmission, distribution, and transformation losses, and own-use consumption of cogeneration facilities, divided by the total population.	kWh per capita	Our World in Data (2026)
EnergyOil	Electricity production from oil is the electricity generated from crude oil and petroleum-derived products.	Percentage	World Bank (2026a)
EnergyRenCon	Renewable energy consumption represents the share of renewable energy in total final energy use.	Percentage	World Bank (2026k)
EnergyRenPro	Indicates the share of electricity generated by renewable power plants relative to total electricity production.	Percentage	World Bank (2026j)

Table 2. Cont.

Variable	Definition	Unit Adopted	Source
Socio-Demographic Variables			
log(Population)	Natural logarithm of total population. The original population variable is based on the de facto definition of population, which includes all residents regardless of legal status or citizenship.	Unitless	Transparency International (2026)
UrbanPop	Urban population as a percentage of total population. It refers to the share of individuals residing in urban areas as defined by national statistical authorities.	Percentage	World Bank (2026n)
UrbanPopGrow	Measures the annual growth rate of the urban population according to national statistical definitions.	Percentage	World Bank (2026m)
UrbanPopDen	Population density calculated as midyear population divided by land area in square kilometers.	People/km ²	World Bank (2026i)
Economic Variables			
GDP_pc	GDP per capita, current US\$. Calculated as gross domestic product divided by midyear population.	US\$ per capita	World Bank (2026e)
FDI	Foreign direct investment (FDI), net inflows (Percentage of GDP).	Percentage	World Bank (2026d)
Exp	Exports of goods and services represents the value of goods and market services supplied to the rest of the world as a percentage of gross domestic product.	Percentage	World Bank (2026b)
Imp	Imports of goods and represents the value of goods and market services received from the rest of the world as a percentage of gross domestic product.	Percentage	World Bank (2026f)
Development-Level Variables			
IMFcredit	Use of IMF credit as a percentage of GDP. It includes drawings made by member countries on the IMF, excluding reserve tranche positions.	Percentage	World Bank (2026o)
ExtDebt	Total external debt as a percentage of GDP. It refers to the sum of long-term public and publicly guaranteed debt normalized by GDP.	Percentage	World Bank (2026c)
Inflation	Measured as the annual growth rate of the GDP implicit deflator, reflecting overall price changes in the economy.	Percentage	World Bank (2026g)
Reserves	Total reserves (including gold) as a percentage of GDP. It comprises monetary gold holdings, Special Drawing Rights (SDRs), IMF reserve positions, and foreign exchange reserves held by monetary authorities.	Percentage	World Bank (2026l)
Migration	Net migration as a share of total population. It represents the net total of migrants during the period, calculated as the number of immigrants minus the number of emigrants, including both citizens and non-citizens, normalized by total population.	Percentage	World Bank (2026h)
Corruption	Corruption Perceptions Index (Scores range from 0 (highly corrupt) to 10 (very clean).	Score	Transparency International (2026)
Dependent Variable			
log(CO ₂ _pc)	Natural logarithm of annual net carbon dioxide (CO ₂) emissions per capita. The original variable is calculated as total annual CO ₂ emissions divided by the total population of the country.	Unitless	Our World in Data (2026)

Specifically, a large share of the macroeconomic, trade, sociodemographic, and energy variables was obtained from the World Development Indicators of the World Bank; CO₂ emissions per capita were taken from Our World in Data; and the corruption indicators were drawn from the Corruption Perceptions Index of Transparency International. ETS-related variables were coded on a country-year basis. For years in which no ETS was in

force, the corresponding ETS value was recorded as zero. Consequently, ETS information enters the analysis only after the corresponding scheme is implemented.

Building a reliable model means selecting variables that truly matter, which is why each indicator we chose is firmly backed by recent evidence on CO₂ emissions. Naturally, the most direct contributors are energy use and human demographics. A country's baseline electricity consumption and its dependence on oil-derived power largely set the floor for its fossil-fuel footprint. On the other hand, bringing renewable energy into the mix, both generating and consuming it, acts as the primary defense, helping to untangle energy demand from carbon pollution (Nnaji et al., 2025). But energy does not exist in a vacuum; it is driven by people. A steadily growing population naturally drives up total energy needs. In developing economies, this pressure is intensified by rapid urban shifts, whether that is the sheer number of people moving to cities, the pace of that growth, or how densely packed those urban areas become, alongside broader migration patterns. Ultimately, these spatial shifts trigger massive bursts of carbon-intensive construction and put heavy strain on local grids, pushing CO₂ levels higher (Lu, 2024).

Yet, physical constraints only tell half the story; a region's economic and institutional landscape is just as decisive. We look at per capita wealth to capture the Environmental Kuznets Curve, essentially testing if nations inevitably pollute more before becoming wealthy enough to clean up. Alongside this, globalization metrics like trade volumes show how plugging into global supply chains and ramping up industrial output directly increase a country's carbon footprint (Zhou et al., 2025). We also track foreign direct investment to see what kind of money is flowing in: is foreign capital turning the country into a "Pollution Haven" for dirty industries, or is it funding the leap to green technologies? Just as importantly, our model factors in deep macroeconomic struggles like heavy external debt, reliance on IMF bailouts, high inflation, and low foreign reserves. When a country is financially squeezed, there is rarely room in the budget for green initiatives; instead, they are often forced to double down on carbon-heavy exports just to pay off international debt (Shang et al., 2025). Finally, we must account for governance. Public sector corruption can quietly dismantle even the best environmental laws. Without genuine institutional integrity, market tools like emissions trading systems easily fall prey to regulatory capture, proving that fighting corruption is an absolute prerequisite for actually cutting carbon (Sundström et al., 2024).

Table 3 summarizes the descriptive statistics of the 22 variables used in the ANN model. In particular, Table 3 presents the mean, standard deviation (Std. Dev.), minimum (Min), and maximum (Max) values for each variable. The data exhibit substantial heterogeneity across countries, particularly in economic and development-related indicators such as GDP per capita, external debt, and reserves. Environmental variables also show wide dispersion, especially in the renewable energy production. Socio-demographic indicators reflect considerable variation in population size and density, while institutional variables indicate that ETS adoption and EU membership are not uniformly distributed across observations. Overall, the variability observed across variables supports the use of a flexible modeling approach to capture complex, non-linear relationships.

Table 3. Descriptive statistics of the variables used in the ANN model.

Variable	Mean	Std. Dev.	Min	Max
Institutional and Temporal Variables				
Year	2010.50	6.35	2000	2021
# ETS	0.60	0.86	0	9
EUmember	0.47	0.50	0	1
Environmental Variables				
EnergyCon_pc	0.00	0.02	0.00	0.17
EnergyOil	7.82	19.12	0.00	100.00
EnergyRenCon	19.74	15.48	0.00	82.90
EnergyRenPro	31.23	26.36	0.00	99.99
Socio-Demographic Variables				
log(Population)	16.70	1.80	12.55	21.07
UrbanPop	70.05	17.96	0.00	95.51
UrbanPopGrow	1.08	1.33	−3.83	10.62
PopDen	153.26	207.53	2.48	1619.22
Economic Variables				
GDP_pc	24,686.33	22,330.40	404.03	134,965.82
FDI	9.15	39.86	−296.01	452.22
Exp	47.32	29.39	9.04	215.62
Imp	45.64	25.17	9.10	181.89
Development-Level Variables				
IMFcredit	0.48	1.78	0.00	15.99
ExtDebt	12.19	23.58	0.00	151.77
Inflation	4.41	6.42	−9.90	53.80
Reserves	14.87	14.23	0.34	146.01
Migration	0.23	0.54	−2.55	4.03
Corruption	5.79	2.15	1.50	10.00
Dependent Variable				
log(CO ₂ _pc)	1.80	0.68	−0.36	3.26

3.2. Data Processing

The dataset used to model the performance gap contained some missing observations in the initial years of the sample. For the Corruption index, missing values were estimated using country-specific polynomial time-trend regressions. A second-degree regression model was applied to Cyprus (2000–2002) and Malta (2000–2003) to account for non-linear temporal dynamics, whereas a first-degree model was used for the Dominican Republic (2000) because the observed series showed no curvature. For Luxembourg, the missing FDI value in 2000 was imputed using a forward-moving average based on the first four available observations.

3.3. Identifying ETS Archetypes Using the *k*-Prototypes Clustering Algorithm

In order to identify archetypes among the ETSs studied, we employ the *k*-prototypes clustering algorithm (Huang, 1997, 1998) to define four clusters, where the number of clusters is determined using the classical elbow method and confirmed through the maximum curvature criterion. This approach allows us to group ETSs by similarity in their structural, regulatory, and maturity characteristics, thereby providing a systematic characterization of ETS design configurations. Identifying such archetypes facilitates a clearer understanding of the institutional and policy environments in which each system operates.

The k -prototypes algorithm extends the traditional k -means (Ikotun et al., 2023; Jin & Han, 2017) framework to consider mixed-type data by combining Euclidean distance for numerical variables with a matching dissimilarity measure for categorical variables. Cluster centroids are defined by means for numerical attributes and modes for categorical attributes. Through an iterative reallocation procedure, the algorithm partitions the 58 ETSs into k clusters by minimizing within-cluster heterogeneity while maximizing between-cluster differentiation.

The identification of archetypes is analytically important for assessing performance gaps. Rather than comparing all ETSs indiscriminately, clustering enables evaluation relative to structurally similar peers. This reduces heterogeneity bias and provides a more meaningful benchmark for interpreting differences in outcomes, particularly when institutional maturity, regulatory scope, and quantitative ambition vary substantially across systems.

While the clustering analysis is used to identify distinct ETS archetypes based on their design features, the relationship between these characteristics and emissions outcomes is examined through an ANN model and the subsequent sensitivity analysis.

3.4. Assessing the Performance Gap Between Economies Using an ANN Model

To evaluate the factors associated with differences in emissions performance across developed and developing economies, we implement an ANN model. This approach allows us to examine the highly nonlinear relationships between environmental, socio-demographic, economic, and development-level variables and carbon emissions per capita in the studied economies. ANNs are particularly well-suited to this context because the interactions among energy structure, economic activity, and institutional characteristics may not follow simple linear patterns (Ghoddusi et al., 2019; Marcjasz et al., 2023; Yamazaki et al., 2022). Figure 2 depicts the model used in this analysis; this model consists of an input layer containing the explanatory variables, two hidden layers with 32 and 16 neurons and using ReLU activation functions, and a single output neuron predicting $\log(\text{CO}_2)$ emissions per capita.

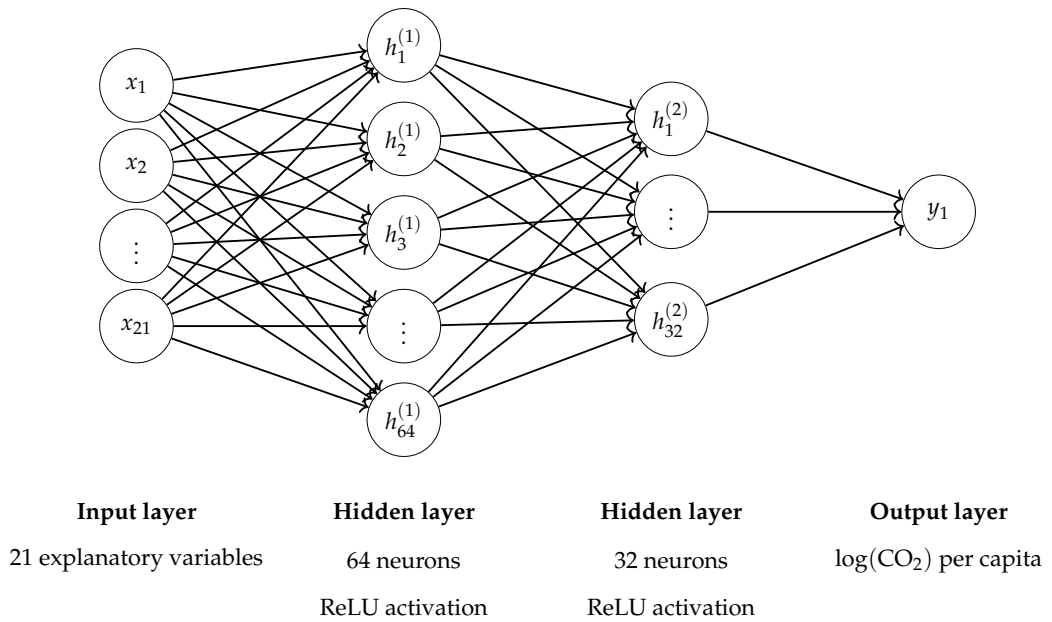


Figure 2. Neural network architecture used in the analysis.

The dependent variable in the model is the logarithm of carbon dioxide emissions per capita. By applying this logarithmic transformation, we reduce skewness and mitigate the influence of extreme values, leading to a more stable variance across observations.

The explanatory variables include indicators related to environmental, socio-demographic, economic, and development-level characteristics. The explanatory variables correspond to the set described in Table 2. Prior to model estimation, all input variables are standardized to ensure numerical stability and improve convergence during training. The dataset contained 1166 observations. Following common practice in machine learning applications, the sample was randomly divided into training (80%) and testing (20%) subsets. Within the training subset, 20% of the observations were further reserved for validation during model training. Consequently, approximately 64% of the observations were used for model fitting, 16% for validation, and 20% for out-of-sample testing.

The ANN is implemented as a feedforward architecture consisting of an input layer, two hidden layers, and a single output neuron. Several ANN architectures were evaluated through a hyperparameter tuning exercise. Specifically, this involved three alternative network structures (16–8, 32–16, and 64–32 neurons in the hidden layers) and three dropout rates (0.1, 0.2, and 0.3). Model selection was based on validation loss and out-of-sample predictive performance. The final ANN architecture consisted of two hidden layers with 64 and 32 neurons, both with rectified linear unit (ReLU) activation, a dropout rate of 0.1, and the Adam optimizer. The use of two hidden layers allows the model to capture more complex nonlinear interactions in a parsimonious way, avoiding the need for an excessively large number of neurons in a single layer. The output layer consists of a single neuron with linear activation to predict the continuous target variable.

The network parameters were selected by considering the mean squared error (MSE) loss function, given by Equation (1). In addition to the MSE, we evaluate the model's predictive accuracy using the mean absolute error (MAE), which measures the average absolute difference between observed and predicted values. The MAE is defined in Equation (2).

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (1)$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (2)$$

where y_i denotes the observed value of log CO₂ emissions per capita and $\hat{y}_i$ the value predicted by the neural network. The index i refers to country-year observations, and N denotes the total number of observations in the dataset.

Table 4 summarizes the best-performing specification for each architecture. The 64–32 architecture with a dropout rate of 0.1 achieved the lowest validation loss (0.0064), the best values for the MSE (0.0082) and MAE (0.0604) tests, and the highest predictive accuracy on the test set ($R^2 = 0.983$). Consequently, this architecture was selected for the final ANN model.

Table 4. ANN architecture tuning results.

Architecture	Dropout	Validation Loss	Test MSE	Test R^2	Test MAE
16–8	0.1	0.0195	0.0181	0.962	0.1079
32–16	0.1	0.0118	0.0110	0.977	0.0775
64–32	0.1	0.0064	0.0082	0.983	0.0604

To mitigate the risk of overfitting, several complementary strategies were implemented. First, the dataset was divided into training, validation, and testing subsets, and model performance was assessed using out-of-sample evaluation metrics, including the Mean Squared Error (MSE) and Mean Absolute Error (MAE). Second, the network architecture was selected through a hyperparameter tuning procedure and kept relatively parsimonious

with respect to the sample size, balancing predictive accuracy and model complexity. Model parameters were estimated using the Adam optimization algorithm with the mean squared error as the loss function. This configuration provides sufficient flexibility to capture nonlinear relationships while reducing the likelihood of overfitting. In addition, a dropout rate of 0.1 was applied between hidden layers, and early stopping was employed using validation loss as the monitoring criterion with a patience value of 200 epochs. The minimum validation loss was achieved at epoch 474, and training terminated automatically at epoch 674 after no further improvement was observed, with the weights corresponding to the best validation performance restored for the final model.

To assess the performance gap between developed and developing economies, we conduct a sensitivity analysis within the ANN model. While panel data models often rely on fixed effects to control for unobserved heterogeneity across countries, the objective of this study is not causal inference but rather the identification of performance differences and nonlinear patterns across heterogeneous ETS contexts. In this setting, the ANN model serves as a predictive tool that captures complex interactions among observed variables. After training the model, we evaluate how variations in each of the explanatory variables affect the predicted values of CO₂ emissions per capita. This approach allows us to identify the relative importance of the variables included in the model. The use of the full sample allows the model to capture the full range of heterogeneity across developed and developing economies, ensuring comparability in the assessment of performance gaps.

The ANN is employed as a predictive and exploratory modeling framework rather than as a causal inference model. Unlike panel-data econometric approaches, the objective of the ANN is not to estimate structural parameters or identify causal effects associated with individual explanatory variables. Instead, the network is used to capture potentially complex and nonlinear relationships among ETS characteristics, energy indicators, socioeconomic variables, and CO₂ emissions. Consequently, the results should be interpreted as predictive associations and sensitivity patterns rather than causal estimates. Finally, the ANN predictions are used to compare emissions performance across groups of countries and across the ETS archetypes identified through the clustering analysis. This integrated approach enables us to evaluate whether differences in the four mentioned dimensions contribute to the observed variation in emissions outcomes across emissions trading systems.

4. Results

4.1. Cluster Characterization

To determine the number of clusters, we estimated the k -prototypes model for k ranging from 2 to 11 and evaluated the within-cluster heterogeneity (cost) function. Figure 3 presents the results of this analysis, and illustrates both selection criteria. In the left panel, the blue curve represents the within-cluster heterogeneity (cost) for different values of k , while the vertical dashed line indicates the selected elbow at $k = 4$. In the right panel, the blue curve shows the normalized clustering cost, and the orange dashed line corresponds to the reference line used by the maximum curvature criterion. The point exhibiting the largest perpendicular distance from this reference line identifies the optimal number of clusters, which is also $k = 4$. While five or more clusters reduce within-cluster dispersion, the incremental gains become progressively smaller, suggesting diminishing returns in model complexity. Accordingly, we apply the classical elbow method and confirm the result using the maximum curvature criterion (Satopaa et al., 2011; Shi et al., 2021), both of which identify $k = 4$ as the best number of clusters. This choice maintains a balance between the number of clusters and their heterogeneity, resulting in the classification of the 58 ETSs into four distinct and interpretable groups. In addition to this quantitative criterion, we consider the interpretability and economic relevance of the resulting clusters. The four-cluster solution

provides a meaningful classification of ETS archetypes, enabling a clear differentiation in terms of institutional maturity, regulatory scope, and structural characteristics.

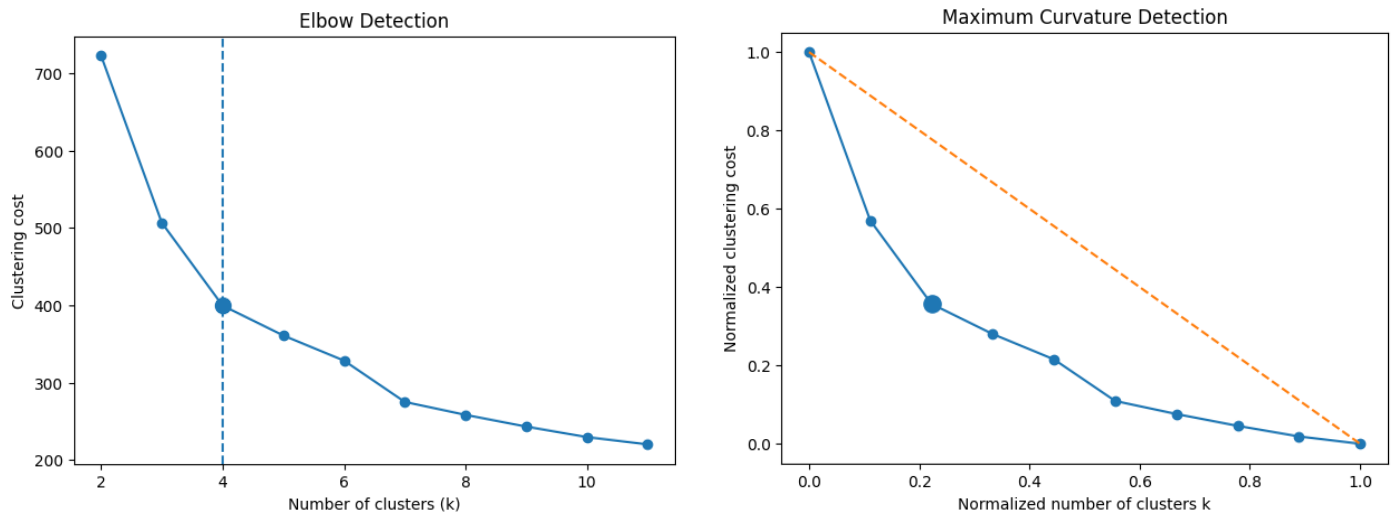


Figure 3. Identification of the number of clusters using elbow analysis and maximum curvature detection.

Table 5 summarizes the results of the k -prototypes clustering algorithm. On the one hand, variables related to institutional maturity are presented as percentages. “In force” is the percentage of ETSs with a status of “In force,” meaning the regulation is legally active, binding, and fully operational. “Penalty in place” refers to the percentage of ETSs that apply an economic penalty per tonne of excess emissions per year. The “Monitoring system” row presents the percentage of ETSs monitoring, reporting, and verification of GHG emissions. On the other hand, variables related to the regulatory scope are also presented as percentages. “Emission limits” refers to the percentage of ETSs that explicitly have an emission limit or capacity. “Multi-gas coverage” includes the ETSs counting several gases, not only CO₂. The “Sector coverage index” is a synthetic measure of the breadth of sectoral inclusion in each ETS. For each economic sector (energy, agriculture, industrial processes, waste, mining, transport, buildings, and maritime), a binary indicator is assigned, taking the value 1 if the sector is covered by the ETS and 0 otherwise. The index is then calculated as the proportion of covered sectors relative to the total number of sectors considered, expressed as a percentage. Finally, Table 5 presents the variables related to structural characteristics. The “Average GHG target” and “Average years of operation” rows each show the average of the corresponding variable across the ETSs in each cluster. The “Developed | Developing economies” row shows the relationship between developed and developing economies within each cluster. The last row captures the total number of ETSs for each cluster.

The cluster analysis reveals a structural differentiation across ETS regimes along dimensions of institutional maturity, regulatory scope, and mitigation scale. While the complete cluster membership is reported in ETS clusters (https://docs.google.com/spreadsheets/d/1nhLIy6F-i92Jmk63soOY_yxLnjrT19rT/edit?usp=sharing&ouid=108590407146840467460&rtfpof=true&sd=true, accessed on 24 February 2026), in this section, we present illustrative examples that highlight the structural differences across groups.

Cluster 1 is composed mainly of ETSs from Asia, predominantly located in developed economies; it groups consolidated and fully operational ETSs, long-standing systems with full legal enforcement, active monitoring frameworks, and strong industrial coverage, including mainly industrial processes, transport, and buildings. Most of the ETSs from

the USA and Latin America are included in Cluster 2. Cluster 2 balances developed and developing economies; most systems remain under development or in draft stages, with only partial regulatory architecture. With respect to its sectoral coverage, Cluster 2 highlights its focus on the agricultural and waste sectors. Cluster 3 is composed mainly of countries from North America (Canada, the USA, and Mexico). Although relatively young, they demonstrate substantial regulatory ambition. These ETSs combine strong enforcement mechanisms with broader multi-gas coverage; their sectoral coverage is marked by the energy and mining industries. Finally, Cluster 4 includes the smallest set of ETSs, all of which are located within developed economies. Cluster 4 is characterized by stable enforcement mechanisms and relatively balanced sectoral inclusion, including the maritime sector, which is not regularly present in the other clusters.

Table 5. Characteristics by ETS Cluster.

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Institutional Maturity (%)				
In force	100	20.8	93.8	100
Monitoring system	100	62.5	100	100
Penalty in place	84.6	25.0	81.3	80.0
Regulatory Scope (%)				
Emission limits	100	12.5	87.5	100
Multi-gas coverage	30.8	37.5	68.8	60
Sector coverage index	42.3	45.3	39.8	45
Structural Characteristics				
Average GHG target	237.2	593.8	1156.1	854.4
Average years of operation	12.7	1.7	5.3	18
Developed Developing economies	12 1	12 12	13 3	5 0
Number of ETS	13	24	16	5

The cluster classification can be illustrated through representative examples. Cluster 1 includes several Chinese pilot ETSs (e.g., Beijing, Shanghai, and Tianjin) as well as the Saitama ETS in Japan, reflecting systems with relatively strong institutional development but limited scale. Cluster 2 comprises developing systems, including those of Chile, Colombia, Argentina, and India. Cluster 3 includes more advanced national systems such as the China National ETS, the German National ETS, and the Australian Safeguard Mechanism. Finally, Cluster 4 contains highly mature and long-established systems, including the EU ETS, the New Zealand ETS, the Swiss ETS, and the Regional Greenhouse Gas Initiative (RGGI) in the United States. From a policy perspective, the results suggest different priorities across clusters. Developing systems should focus on strengthening monitoring, reporting, verification, and enforcement mechanisms. Intermediate systems may benefit from expanding sectoral coverage and improving market efficiency. Mature systems should prioritize more ambitious emissions caps, stronger integration with renewable-energy policies, and enhanced cooperation across carbon markets.

Figure 4 presents the average values (for continuous variables) and proportions (for binary variables) of key features across the four clusters identified using the *k*-prototypes algorithm. Each row corresponds to a variable used in the clustering process, while columns represent clusters. The heatmap highlights systematic differences in institutional maturity, regulatory scope, sectoral coverage, and structural characteristics across clusters. Cluster 1 is characterized by high institutional maturity and full implementation of emission limits and monitoring systems. Cluster 2 groups ETSs in earlier stages of development, with lower regulatory coverage and weaker institutional features. Cluster 3 represents systems

with broad sectoral coverage. Cluster 4 includes mature systems with long operational histories and comprehensive regulatory frameworks.



Figure 4. Heatmap of ETS cluster profiles.

Overall, the results indicate that ETS heterogeneity is not solely driven by regulatory design and institutional maturity, but also by economic development status.

4.2. Role of Country Context

4.2.1. Feature Importance Analysis

To identify the variables that contribute most strongly to the ANN predictions, we complemented the sensitivity analysis with two feature-importance techniques: permutation importance and SHAP (SHapley Additive exPlanations) values. Both methods produced highly consistent rankings. To obtain a robust measure of variable relevance, their scores were normalized to a common 0–1 range. A combined feature-importance index was then computed as the arithmetic mean of the normalized SHAP and permutation importance scores. This procedure provides a more robust assessment of variable relevance by integrating both global predictive importance and local contribution information.

The results given in Table 6 indicate that approximately 80% of the model’s explanatory power is concentrated in ten variables: renewable energy consumption, corruption, exports, GDP per capita, renewable energy production, population size, population density, external

debt, urbanization, and energy consumption per capita. Among these, renewable energy consumption and corruption emerge as the most influential predictors of CO₂ emissions.

Table 6. Top 10 variables according to combined SHAP and permutation importance scores.

Rank	Variable	Permutation	SHAP	Combined Score	Cumulative Importance
1	EnergyRenCon	0.1967	0.2211	0.2489	0.2489
2	Corruption	0.1230	0.1114	0.1411	0.3900
3	Exp	0.0504	0.0767	0.0747	0.4647
4	GDP_pc	0.0322	0.0691	0.0586	0.5233
5	EnergyRenPro	0.0475	0.0470	0.0567	0.5800
6	log(Population)	0.0458	0.0415	0.0525	0.6325
7	PopDen	0.0337	0.0512	0.0499	0.6824
8	ExtDebt	0.0263	0.0532	0.0462	0.7286
9	UrbanPop	0.0386	0.0240	0.0383	0.7669
10	EnergyCon_pc	0.0321	0.0292	0.0369	0.8038
11	Remaining variables	0.1380	0.1962	0.1962	1.0000

Note: SHAP values and permutation importance scores were first normalized to a 0–1 scale. The combined score corresponds to the arithmetic mean of the normalized SHAP importance and normalized permutation importance for each variable. Variables are ranked according to this combined score.

These findings reinforce the conclusions obtained from the sensitivity analysis. In particular, they highlight the central role of energy-transition variables, institutional quality, trade activity, and demographic factors in shaping environmental performance. Conversely, variables such as IMF credit, reserves, inflation, foreign direct investment, and ETS participation exhibit comparatively lower importance scores. Nevertheless, these variables were retained because they represent theoretically relevant dimensions of economic development, institutional capacity, and environmental policy.

4.2.2. Feature Sensitivity Analysis

Table 7 presents the sensitivity analysis of the ANN model, reporting the percentage change in predicted CO₂ emissions per capita resulting from perturbations in the explanatory variables. The sensitivity analysis is performed using observed country-year data. For each row, the corresponding explanatory variable is perturbed by $\pm 5\%$, $\pm 15\%$, and $\pm 30\%$, while all other variables are held constant at their observed values. The last two columns summarize the functional form of the relationship between each variable and CO₂ emissions per capita. Specifically, “lin” denotes a linear relationship, “log” indicates a logarithmic relationship, and “exp” corresponds to an exponential pattern. The superscripts “+” and “−” indicate whether the relationship is positive or negative, respectively. A dash (—) denotes that no clear trend was identified based on the goodness-of-fit criteria. The resulting changes in predicted emissions are computed and averaged across all observations within each group. The results are reported separately for developed (Devd.) and developing (Devg.) economies, allowing us to assess how structural differences influence the responsiveness of emissions to environmental, socio-demographic, economic, and institutional factors.

The sensitivity analysis reveals highly heterogeneous outcomes, demonstrating that the predictive behavior of the variables follows distinct patterns depending on whether the context is a developed or a developing economy. By simulating variations in these key metrics, the model yields the following responses across different dimensions: Renewable Energy Consumption (EnergyRenCon): Starting with the environmental dimension, this variable exhibits a strong inverse relationship with forecasted emissions. When consumption is decreased by 30%, the model predicts an upward shift in CO₂ levels of 7.31% for developed countries, whereas in developing nations, this projection climbs much more

steeply by 12.56%. Conversely, simulating a 30% increase yields a symmetrical reduction in CO₂ forecasts: −7.23% for developed economies and −7.33% for developing ones.

Table 7. Sensitivity results of the ANN model.

Variable	−30		−15		−5		5		15		30		Trend	
	Devd.	Devg.	Devd.	Devg.	Devd.	Devg.	Devd.	Devg.	Devd.	Devg.	Devd.	Devg.	Devd.	Devg.
Environmental Variables														
EnergyCon_pc	−0.71	−0.02	−0.39	−0.01	−0.14	−0.00	0.15	0.00	0.48	0.01	1.06	0.02	exp ⁺	log ⁺
EnergyOil	0.10	0.68	0.01	0.27	−0.00	0.08	0.01	−0.06	0.03	−0.17	0.13	−0.25	—	log [−]
EnergyRenCon	7.31	12.56	3.60	4.89	1.20	1.44	−1.19	−1.37	−3.62	−3.90	−7.23	−7.33	log [−]	log [−]
EnergyRenPro	1.37	3.60	0.40	1.71	0.11	0.54	−0.06	−0.48	−0.10	−1.27	0.01	−2.42	—	log [−]
Socio-Demographic Variables														
log(Population)	52.71	67.01	15.85	12.09	3.02	−0.76	−0.36	4.87	2.97	23.92	9.90	73.85	—	—
UrbanPop	−3.67	2.90	−1.32	0.08	−0.14	−0.60	−0.03	0.94	0.01	3.97	1.37	12.54	log ⁺	—
UrbanPopGrow	0.38	2.35	0.21	1.05	0.07	0.33	−0.07	−0.29	−0.23	−0.83	−0.47	−1.54	exp [−]	log [−]
PopDen	1.35	3.62	0.68	1.64	0.23	0.52	−0.23	−0.49	−0.72	−1.43	−1.53	−2.74	exp [−]	log [−]
Economic Variables														
GDP_pc	−3.21	−0.81	−1.36	−0.41	−0.41	−0.14	0.39	0.14	1.14	0.43	2.28	0.88	log ⁺	exp ⁺
FDI	0.05	−0.04	0.01	−0.02	0.00	−0.01	0.00	0.01	0.01	0.02	0.02	0.04	—	log ⁺
Exp	−4.11	−3.36	−2.27	−1.88	−0.81	−0.66	0.90	0.69	3.01	2.22	6.96	4.85	exp ⁺	exp ⁺
Imp	3.24	1.67	1.49	0.72	0.46	0.23	−0.43	−0.22	−1.32	−0.54	−2.73	−0.80	log [−]	log [−]
Development-Level Variables														
IMFcredit	0.08	0.43	0.03	0.18	0.01	0.06	−0.01	−0.05	−0.03	−0.15	−0.05	−0.27	log [−]	log [−]
ExtDebt	0.06	1.38	0.03	0.48	0.01	0.12	−0.02	−0.08	−0.05	−0.19	−0.08	−0.24	exp [−]	log [−]
Inflation	0.17	−1.00	0.09	−0.46	0.03	−0.15	−0.03	0.15	−0.09	0.41	−0.19	0.77	exp [−]	log ⁺
Reserves	0.20	0.97	0.09	0.44	0.03	0.13	−0.02	−0.12	−0.07	−0.34	−0.12	−0.53	log [−]	log [−]
Migration	−0.30	0.04	−0.16	0.01	−0.05	0.00	0.06	0.00	0.19	0.02	0.39	0.06	exp ⁺	—
Corruption	−7.38	−4.15	−4.33	−2.29	−1.67	−0.81	2.03	0.89	7.19	3.04	17.78	7.30	exp ⁺	exp ⁺

Corruption: This institutional variable also displays a notable influence on the algorithm's output. If corruption levels are reduced by 30%, the model anticipates a 7.38% decrease in CO₂ emissions for developed nations. On the other hand, an upward variation of 30% in corruption yields a substantial surge in projected emissions, rising by 17.78% in developed countries and 7.30% in developing nations. Regarding economic indicators, exports (Exp) exhibit a direct, positive correlation with the emission forecasts. For instance, a 15% reduction in exports translates into a decrease in predicted carbon emissions of 4.11% in developed countries and 3.36% in developing economies. Reversing this scenario, a 30% increase in exports leads the network to project higher CO₂ levels, moving up by 6.96% and 4.85% for developed and developing nations, respectively.

Renewable Energy Production (EnergyRenPro): When simulating a 30% decline in this variable, the model registers an increase in CO₂ forecasts of 1.37% in developed countries and 3.60% in developing ones. Interestingly, introducing a 30% upward variation produces mixed responses: it prompts a negligible increase of 0.01% in developed nations, whereas developing countries register a clear 2.42% decrease in their projected emissions.

Urban Population: Finally, shifts in urban population (UrbanPop) show a well-defined correlation with the model's outputs. A 30% decline in this metric lowers the forecasted carbon emissions by 3.67% in developed nations and 2.90% in developing ones. Conversely, when the urban population is scaled up by 30%, the projections rise asymmetrically: developed economies see a modest 1.37% increase, while developing nations experience a much more pronounced surge of 12.54% in their CO₂ forecasts.

Although the ANN is not designed to estimate causal effects, feature-importance analysis indicates that renewable energy consumption, corruption, exports, GDP per capita, and demographic factors are among the variables that contribute most strongly to the model's predictions. Instead, its primary purpose is to analyze the interrelationships

among structural, economic, social, and institutional factors that shape emission dynamics, allowing for a more comprehensive understanding of the phenomenon. In this context, the model contributes to the analysis of performance gaps in environmental instruments, particularly ETs, between developed and developing economies. The findings indicate that the effectiveness of these mechanisms depends not only on their design or on environmental taxation, but also on a broader set of structural conditions that define the context in which they operate. Additionally, the analysis shows that not all variables exert the same level of influence. Factors such as population, inflation, and external debt exhibit relatively limited effects. However, rather than diminishing their relevance, these results highlight that even variables with lower individual influence contribute to a more comprehensive understanding of environmental behavior and should be considered in integrated modeling approaches. In particular, the study emphasizes the importance of institutional factors such as corruption, which can significantly constrain the implementation and enforcement of environmental policies. Therefore, the analysis of environmental performance should not be limited to emission metrics or economic instruments alone but should incorporate additional dimensions that enable a more complete understanding of the determinants of environmental outcomes across different development contexts.

5. Discussion

The results of this study suggest that the environmental performance of ETs depends not only on the existence of carbon markets, but also on the combination of various institutional, energy-related, economic, and demographic factors. In particular, the importance of variables such as renewable energy consumption, renewable energy production, corruption, and urbanization highlights the role of complementary conditions that may influence the effectiveness of carbon pricing mechanisms. Therefore, the following discussion compares the main findings with previous literature and analyzes their implications for policymakers, firms, and future research on carbon markets.

The negative relationship observed between renewable energy consumption, renewable energy production, and CO₂ emissions is consistent with previous studies that identify renewable energy as one of the main drivers of decarbonization. Similar findings have been reported by Volodzquienė and Streimikiene (2026), Song et al. (2026), and Ahuja et al. (2025), who argue that greater reliance on renewable energy sources significantly contributes to reducing carbon emissions. The consistency between the results of this study and previous evidence suggests that renewable energy continues to serve as a cornerstone mechanism through which ETs can achieve their environmental objectives, particularly in developing economies.

The results indicating a stronger relationship between corruption and emissions in developing economies are consistent with the findings of Montes and Landim (2026), who report that weak governance structures reduce the effectiveness of environmental regulations and hinder compliance with climate policies. In the context of ETs, this finding suggests that institutional quality remains a critical condition for achieving meaningful emissions reductions. The stronger effect observed in developing economies may be associated with differences in regulatory enforcement capacity and overall governance effectiveness.

The findings of this study suggest that environmental regulators in developing economies should avoid implementing ETs as isolated policy instruments. Instead, the development of carbon markets should follow a structured and sequential approach. First, governments should strengthen institutional quality and, more importantly, enhance the monitoring capacity of these systems, given the significant influence that factors such as corruption exert on environmental performance. Second, public policies should prioritize the deployment and consumption of renewable energy, as these variables emerge

as the most influential determinants associated with lower CO₂ emissions. Finally, the expansion of ETSs should focus on export-oriented sectors with high carbon intensity. In this context, complementary urban sustainability policies should also be implemented to mitigate the emissions pressures associated with urban population growth and increasing population density.

From the perspective of firms operating under ETS frameworks, the results indicate that decarbonization strategies should primarily focus on the adoption of renewable energy and the pursuit of greater energy efficiency. Sustainability accounting systems should increasingly incorporate carbon exposure associated with energy consumption, export activities, and operational footprints in urban environments. Likewise, green investment decisions should prioritize technologies capable of reducing dependence on fossil-fuel-based energy sources, as these factors explain a substantial proportion of the differences in environmental performance across jurisdictions operating under ETS frameworks.

From a research perspective, the findings of this study demonstrate the importance and value of combining machine learning techniques with carbon market analysis. Rather than relying exclusively on traditional econometric approaches, researchers should explore alternative analytical methods such as clustering techniques, artificial neural networks, permutation-based importance analysis, and SHAP-based interpretation, among others, which enable the identification of complex nonlinear relationships among environmental, institutional, and economic variables. Future studies may further expand this methodological framework by incorporating carbon prices, sector-level emissions, and causal inference approaches to improve the understanding of ETS effectiveness.

The sensitivity results can also be directly linked to the Sustainable Development Goals (SDGs). Given the focus of this study, particular emphasis is placed on SDG 7 (Affordable and Clean Energy), as the relevance of renewable energy consumption and renewable energy production is closely aligned with Targets 7.2 and 7.3, which seek to increase the share of renewable energy and improve energy efficiency. Likewise, the importance of variables such as corruption, exports, and urbanization highlights their connection with SDG 13 (Climate Action), particularly the targets aimed at strengthening climate governance, enhancing mitigation capacity, and integrating climate considerations into development strategies. These findings suggest that the effectiveness of ETSs contributes not only to emissions reductions but also to the achievement of broader sustainable development objectives.

Policy Implications

The primary function of an ETS is to establish an emissions cap and impose a financial cost when regulated industries exceed this limit, thereby incentivizing reductions in CO₂ emissions within the industrial sector and, consequently, decreasing total annual carbon emissions at the national level. However, based on the results derived from the neural network model, it is evident that achieving a substantial reduction in carbon emissions requires more than the isolated implementation of a single environmental instrument.

The findings indicate that renewable energy production and consumption play a fundamental role in the decarbonization of national economies. Therefore, reinforcing environmental mechanisms within broader public policy frameworks, particularly in developing economies, is essential. To amplify the effectiveness of ETS implementation, the required complementary policy measures have been categorized in Table 8 according to their implementation timeframe, political feasibility, and the specific ETS jurisdictions they target.

Table 8. Strategic Matrix of Complementary ETS Policy Recommendations.

Implementation Timeframe	Political Feasibility	Target ETS Group	Policy Measure & Specific Mechanisms
Short-Term	High (<i>Broad consensus, lower structural barriers</i>)	All Jurisdictions (<i>Crucial for Developing Economies</i>)	Strengthen Environmental Governance: Enhance the implementation and compliance of ETS policies through robust monitoring, reporting, and independent verification (MRV) mechanisms. This includes deploying digital platforms and integrating corruption indicators to ensure transparency.
Medium-Term	High (<i>Attractive to private sector and foreign markets</i>)	Developing Economies (FDI focus) Developed (Innovation focus)	Incentivize Investment & Tech Innovation: Promote Foreign Direct Investment (FDI) and domestic investment in the energy sector to facilitate the establishment of clean energy companies. This should be driven by fiscal and financial incentives, government support programs, tax benefits, preferential interest rates, and mechanisms that foster green technological innovation.
Medium-Term	Low (<i>Often faces resistance from established state monopolies</i>)	Developing & Transitioning Economies	Implement Regulatory Energy Reforms: Overhaul existing energy legislation to reduce entry barriers, explicitly allowing and encouraging greater private sector participation in renewable energy generation.
Long-Term	Low (<i>Requires heavy budgetary reallocation and structural shifts</i>)	All Jurisdictions	Advance Comprehensive Market Reforms: Execute deep, structural energy market reforms that incorporate sustained public investment and strict budget allocation strategies specifically aimed at financing the long-term creation of renewable energy enterprises.

The overarching objective of these categorized measures is to systematically reinforce domestic demand for sustainable energy while aligning national energy policies with global sustainability goals. Consequently, a vital avenue for future research emerging from this analysis involves assessing the real-world feasibility of these proposed implementations. Future studies should determine which specific types of energy reforms are viable for individual economies, identifying the unique structural constraints and opportunities that arise in different national contexts. Finally, subsequent research must consider incorporating updated data on the full spectrum of GHG emissions rather than focusing solely on carbon emissions to provide a more comprehensive assessment of the variables influencing climate performance and to better capture the multifaceted drivers of global warming.

6. Conclusions

The results of the ANN model sensitivity analysis revealed that the development context remains a relevant factor to consider in understanding the trajectory of CO₂ emissions. In this regard, it is important to highlight renewable energy consumption and renewable energy production, as both are consistently associated with lower emissions, with more pronounced effects in developing economies. On the other hand, sociodemographic variables linked to urbanization reflect greater emissions pressures, especially in developing contexts, suggesting that urban growth without sufficient energy infrastructure may constrain the environmental outcomes expected from ETS implementation.

It is important to emphasize a particularly relevant finding of this study: population size shows a differentiated pattern across groups of countries. While in developing economies population growth is associated with marked increases in CO₂ emissions, in developed economies, this effect is smaller and, under certain scenarios, is even associated

with slight reductions in emissions. This result suggests that the issue does not lie in the population itself, but rather in the structural capacity of economies to manage demographic growth through elements such as infrastructure, energy efficiency, transport systems, and solid regulatory frameworks. Therefore, the link between population and emissions should not be interpreted in a linear or universal way, but rather in light of the development context in which the ETS operates.

Furthermore, the economic dimension indicates that international trade is an important component of the environmental performance observed. Exports stand out because of their stronger association with higher emissions in both groups of countries, while imports show a differentiated pattern: in developed economies, they are associated with lower emissions, whereas in developing economies, they are linked to higher CO₂ levels. Within this dimension, one additional factor must be considered: corruption. Corruption emerges as a critical institutional factor in environmental performance. The sensitivity analysis shows that a 30% increase in corruption is associated with a 17.78% increase in emissions in developing economies, whereas in developed economies, the corresponding increase is 7.30%. Conversely, a 30% reduction in corruption is associated with a 4.15% decrease in emissions in developing economies. These results reinforce the idea that the effectiveness of ETSs depends on several factors, including both their design and the quality of the institutional environment. In contexts with higher levels of corruption, problems related to compliance, monitoring, and regulatory enforcement may considerably weaken the instrument's capacity to reduce CO₂ emissions.

In conclusion, the findings indicate that ETSs should not be conceived as self-sufficient instruments. In other words, the effectiveness of their implementation depends on complementary policies that strengthen renewable energy use, environmental governance, and the management of pressures associated with urbanization and trade structures. Thus, assuming that a successful ETS can be mechanically replicated in any context would be a mistake, since both its design and its outcomes depend on specific structural conditions.

Limitations and Future Research Directions

Some limitations of this study should be taken into account when interpreting the findings. First, the ANN model was employed as a predictive and exploratory tool designed to identify nonlinear relationships, variable importance patterns and differences across heterogeneous contexts; therefore, the results should be interpreted as predictive associations rather than causal effects. Unlike conventional panel-data econometric models, the ANN framework does not explicitly account for country fixed effects. Therefore, part of the variation captured by the model may reflect unobserved country-specific characteristics that are not fully represented in the available explanatory variables. To mitigate this concern, the model incorporates a broad set of economic, demographic, institutional, trade, and energy-related indicators that capture important dimensions of cross-country heterogeneity; nevertheless, the results should not be interpreted as evidence of causal relationships.

Second, the dependent variable focused on CO₂ emissions per capita. While this improves cross-country comparability, it does not fully capture the joint behavior of the broader set of greenhouse gases regulated by different ETSs. It is important to note that the available database covers the period from 2000 to 2021 and therefore does not capture recent developments in emissions trading systems implemented after 2021. Third, the analysis does not include carbon price variables, despite carbon pricing being one of the main mechanisms through which ETSs influence emissions reductions.

Based on these limitations, several avenues for future research emerge that could broaden the analysis in different directions. First, it would be useful to incorporate more recent information and consider the full set of greenhouse gases rather than focusing only

on CO₂. Second, it would be valuable to include other variables related to the internal functioning of ETSs, such as carbon prices, effective sectoral coverage, allowance allocation, penalties, reporting systems, and verification mechanisms. Finally, future studies could complement this ANN framework with causal methodologies in order to better isolate the effect of ETSs from other policies and exogenous factors.

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