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INTERPRETABLE CAUSAL MACHINE LEARNING EVIDENCE ON THE IMPACT OF RENEWABLE ENERGY ON CO_2 EMISSIONS

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ABSTRACT

This study examines the impact of renewable energy share on per capita CO_2 emissions using a combination of machine learning-based causal inference and explainable artificial intelligence methods. The relationship between renewable energy and carbon emissions has mostly been addressed in the literature using correlation-based approaches. However, the magnitude, direction, and inter-country variability of the causal effect between renewable energy and carbon emissions remain largely unclear. This study aims to fill this gap. Analyses were conducted using a global panel dataset covering the post-1995 period. In this study, the causal effect of renewable energy share on CO_2 emissions was estimated using the Causal Forest method within the Double Machine Learning framework. Furthermore, the mechanisms behind the obtained heterogeneous treatment effects were interpreted using SHapley Additive exPlanations-based explainability analysis. The findings show that an increase in the share of renewable energy significantly and causally reduces per capita CO_2 emissions on average. The negative conditional mean of treatment effects for all observations reveals that renewable energy transition does not lead to an increase in emissions under any economic or structural conditions. However, the magnitude of the effect differs significantly between countries. Explainable causality analysis shows that energy intensity is the most dominant determinant of this heterogeneity; per capita income and industrial structure play nonlinear and context-sensitive roles. The analysis conducted for Turkey reveals that structural constraints limit the effectiveness of renewable energy transition in middle-income and energy-intensive economies. Overall, this study demonstrates the causal effect of renewable energy policies on emission reduction not only at the average level but also in a heterogeneous and explainable manner. By combining causal inference with explainable machine learning, the study offers a new and powerful empirical framework for evaluating energy and climate policies.
Keywords: CO2 Emissions, Renewable Energy, Interpretable Causal Machine Learning, Causal Inference
JEL Classification: C45, Q42, Q53

1. INTRODUCTION

Combating climate change and global warming is one of the most important global policy and sustainability issues of our time. Energy production and consumption are key elements of this struggle, and carbon emissions from fossil fuel-based energy systems are considered one of the main causes of global warming. Therefore, the transition to renewable energy sources stands out as a fundamental solution both in the literature and in sustainability policies. In recent years, with the widespread adoption of solar, wind, and other renewable energy technologies, numerous studies have been published examining the impact of renewable energy share on carbon emissions (Sadorsky, 2009; Apergis & Payne, 2014; Dogan & Seker, 2016; Dong et al., 2018; Zafar et al., 2020; Pata, 2021).

In the current literature, the relationship between renewable energy and CO_2 emissions is mostly addressed through panel regressions, time series analyses, and various machine learning-based predictive models (Shahbaz et al., 2015; Acheampong et al., 2019). While a significant portion of these studies present strong evidence that increased renewable energy use reduces emissions, they largely rely on correlation-based results. However, from a policy design perspective, the critical question is whether the increase in the share of renewable energy truly reduces emissions causally, independently of other factors. In short, whether the observed relationship reflects a causal effect or whether this relationship is a consequence of concurrent factors such as the economic development, industrial structure, or energy efficiency of countries is a crucial point to examine from a policy standpoint.

This causality issue points to a significant gap in the renewable energy literature. While classical econometric approaches can control for certain confounding variables, they are limited in systems composed of energy, economic, and environmental components where complex and nonlinear relationships prevail. In recent years, machine learning methods have been increasingly used in this field; however, most of these studies have focused on prediction accuracy, leaving their capacity for causal interpretation limited (Sarkodie & Ozturk, 2020; Molnar, 2020). Furthermore, machine learning models, criticized as "black boxes," often fail to meet the need for explainability and interpretability required by policymakers.

In this context, recently developed causal machine learning approaches offer a significant methodological opportunity for the energy and environment literature by enabling more reliable causal inferences under high-dimensional data (Athey & Imbens, 2016; Chernozhukov et al., 2018). Methods such as Double Machine Learning (DML) and Causal Forest allow for consistent prediction of causal effects even in high-dimensional data structures. However, the use of these methods in the context of energy transition is still limited, and studies explaining why and under what conditions the obtained causal effects change are quite few. This situation further highlights the disconnect between causal prediction and explainability.

This study aims to fill this gap. It examines the impact of renewable energy share on per capita CO_2 emissions using a combination of machine learning-based causal inference and explainable artificial intelligence methods. On a global panel dataset covering the period 1995-2020, the causal effect of renewable energy share on emissions is estimated using the Causal Forest method within the DML framework. Furthermore, the mechanisms behind the heterogeneous treatment effects observed across countries are interpreted using SHAP (SHapley Additive exPlanations) based explainability analysis. This approach reveals not only the average effects but also how the causal effect can vary from country to country.

The study offers three main contributions to the literature. Firstly, it evaluates the impact of renewable energy share on CO_2 emissions within a causal framework, going beyond correlation-based approaches. Secondly, it combines causal machine learning methods with explainable artificial intelligence techniques to reveal the structural mechanisms behind heterogeneous treatment effects. Thirdly, through a country-by-country analysis conducted for Turkey, the study concretely reveals the structural constraints under which the renewable energy transition is shaped in middle-income and energy-intensive economies. In these respects, the study aims to establish a new point of reference for interpretable causality-based empirical analyses in the energy transition literature.

The rest of the article is structured as follows: The second section introduces the dataset and methodological framework used. The third section presents the findings, and the fourth section discusses these findings from a causal and structural perspective. The final section summarizes the main conclusions of the study and addresses implications for policy and future research.

2. METHODOLOGY

2.1. Data Set and Variables

In this study, the impact of the share of renewable energy on per capita CO_2 emissions was analyzed using a global panel data set covering the period 1995–2020. The analysis period was limited to the post-1995 period to ensure data continuity and to cover the years when modern energy transition policies intensified.

The data set consists of annual observations at the country level, and per capita CO_2 emissions per capita was used as the dependent variable. The treatment variable is the share of renewable energy in the total energy consumption of the countries. The share of renewable energy is considered a direct indicator of energy transition. In order to accurately estimate the causal relationship, a number of confounding variables were included in the analysis in line with the literature and theoretical framework. These variables include GDP (gross domestic product) per capita, the share of industrial value added in GDP, energy intensity, and year. These variables represent key economic and structural factors that can simultaneously impact both renewable energy investments and carbon emissions.

2.2. Causal Framework and Directed Acyclic Graph (DAG)

The methodological framework of this study is based on an explicit causal assumption. This assumption is visualized in Figure 1 through a directed acyclic graph (DAG). In this framework, the share of renewable energy in total energy consumption is considered as an intervention variable that can be directly associated with policy, while per capita CO_2 emissions are defined as the outcome variable. Per capita gross domestic product, the share of industrial value added in GDP, and energy intensity are identified as key confounding variables that simultaneously affect both renewable energy use and carbon emission levels. In addition, a time variable is included in the model to represent global technological developments, international climate policies, and common shocks affecting all countries over time. The constructed DAG structure shows that if these variables are not controlled, backdoor pathways will open in the relationship between the share of renewable energy and CO_2 emissions, leading to biased predictions. Therefore, by conditioning to the defined set of adjustments, all non-causal paths are closed, and it becomes possible to consistently estimate the average treatment effect of the renewable energy share on per capita CO_2 emissions under standard confounder independence assumptions. This causal structure forms the methodological basis for the dual machine learning and causal forest analyses applied in the remainder of the study.

This framework guided the selection of control variables used in the analysis and helped ensure the conditional independence assumption necessary for causal inference. The DAG-based approach ensures that the model specification is based on a theoretically justified causal structure, not an arbitrary one.

Figure 1 shows the directed non-cyclic graph (DAG) structure created to define the causal effect of renewable energy transition on per capita CO_2 emissions. In the diagram, the share of renewable energy in total energy consumption is defined as the intervention (treatment) variable, and per capita CO_2 emissions are defined as the outcome variable. Per capita GDP, the share of industrial value added in GDP, and energy intensity; Both renewable energy share and CO_2 emissions are included in the model as common confounding variables. The time variable represents common time effects affecting all countries, such as global technological developments and international policy trends. The arrows shown represent hypothetical causal relationships between the variables, and the adjustment set determined in accordance with this structure allows for an unbiased estimation of the causal effect of renewable energy share on CO_2 emissions.

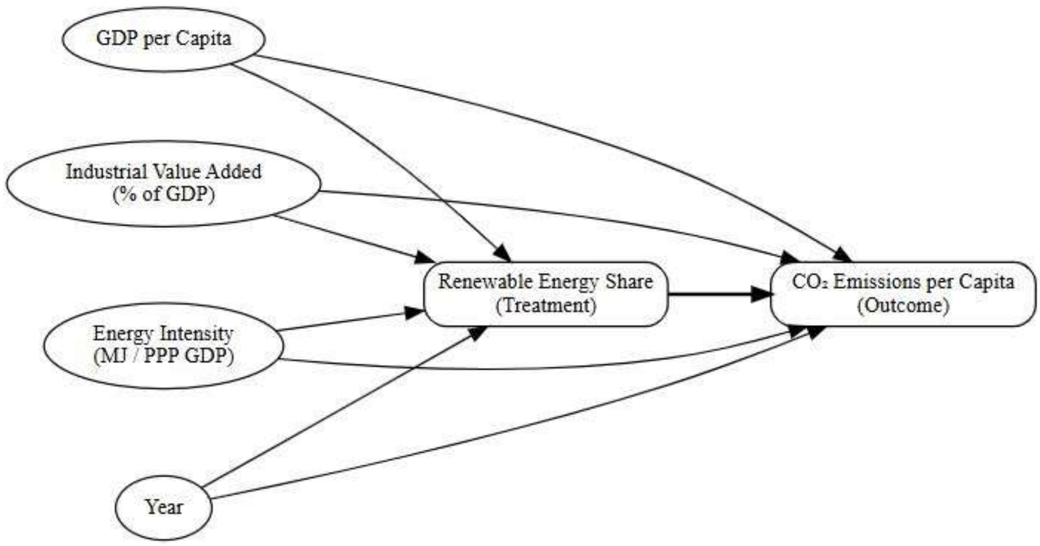

Figure 1: Directed acyclic graph (DAG) illustrating the causal structure between renewable energy share and CO_2 emissions per capita

2.3. Double Machine Learning

To estimate the causal effect of renewable energy share on CO_2 emissions, the Double Machine Learning (DML) method was chosen, as it allows for the elimination of bias in causal effect estimations, even in cases with high-dimensional and nonlinear relationships. In this framework, the outcome variable (CO_2 per capita) and the treatment variable (renewable energy share) were modeled separately using confounding variables; then, the causal effect was estimated from the residuals obtained from these models. This two-stage structure aims to leverage the flexibility of machine learning models while preventing biases caused by overfitting.

The DML framework was applied in accordance with the causal structure defined by the DAG, and key confounding variables such as GDP per capita, industrial value added, and energy intensity were included in the model. This solution allows for the causal assessment of the effects of individual energy conversions on carbon emissions, separating them from the overall results.

2.4. Heterogeneous Causal Effects and Causal Forest

The dual machine learning approach offers a powerful framework for estimating the average causal effect of the share of renewable energy on per capita CO_2 emissions, but it implicitly assumes that this effect is homogeneous across countries. However, the effects of energy transition can differ significantly depending on the structural characteristics of countries, such as their level of economic development, industrial structure, and energy efficiency. Therefore, in this phase of the study, the Causal Forest method was used to examine the heterogeneity of the causal effect. Causal Forest is a version of the random forest algorithm adapted to causal inference and allows for flexible estimation of CATE (conditional average treatment effects). This approach reveals under what conditions the effect of the share of renewable energy on CO_2 emissions is stronger or weaker by iteratively subdividing the sample according to specific characteristics. Thus, instead of a single average effect estimate, differentiated causal effect profiles are obtained at the country level. In this study, causal forest analysis was applied in a manner consistent with the dual machine learning framework and under the condition of confounding variables determined by the DAG structure. GDP per capita, the share of industrial value added in GDP, and energy intensity were included in the model as key structural variables that play a role in explaining heterogeneity.

Through this method, the impact of increasing the share of renewable energy on CO_2 emissions could be estimated separately for each country-year observation. The resulting CATE values reveal under which economic and structural conditions the renewable energy transition has stronger or weaker effects.

2.5. Interpretable Causal ML with SHAP Analysis

In recent years, with the widespread adoption of machine learning methods in the sustainability and energy literature, the explainability of model outputs has become a significant research topic. However, much of the current research addresses explainability only through models based on prediction performance; the interpretations obtained are generally limited to correlation-based relationships. This makes it difficult, especially for policymakers and decision-makers, to clearly understand which variables are effective in the cause-and-effect relationship. The fundamental originality of this study lies in its application of a machine learning-based explainable causality approach by addressing the concept of explainability directly within the framework of causal inference.

In this context, the impact of renewable energy share on per capita CO_2 emissions is interpreted not only with average or conditional estimates but also with direct causal treatment effects. Conditional average treatment effects (CATE) estimated using the causal forest method differ significantly depending on the economic and structural characteristics of countries.

Specifically, the SHAP (SHapley Additive exPlanations) method was used to examine which variables shape and influence CATE values. In this approach, CATE values are treated as dependent variables, and the contributions of confounding variables to this causal effect are separated through SHAP values. The explainability approach used in this study differs conceptually from classical SHAP analyses. While traditional SHAP applications explain the contributions of a machine learning model to the predicted outcome variable, in this study, SHAP values are directly applied to the predicted causal treatment effects. Thus, not only the existence of the effect of renewable energy share on CO_2 emissions, but also why and under what conditions it changes, can be systematically explained. In addition, the SHAP analyses conducted for Turkey demonstrate, through a concrete example, how explainable causality can be used in a practical policy context. Therefore, it is possible to interpret why an increase in the share of renewable energy affects CO_2 emissions more or less in a particular country or group of countries through structural and economic factors.

In conclusion, this study contributes to the literature on explainable artificial intelligence in terms of both the interpretation of model outputs and the explainability of causal effects. This work reveals, through an interpretable causality machine learning approach, under what conditions policy interventions related to energy transition are more effective. In this context, the study provides directly applicable information to decision-makers in the design of sustainability-oriented business and energy policies.

2.6. Methodological Contribution

The methodological approach of this study combines three fundamental elements: the DAG structure, which represents an explicit causal assumption; dual machine learning and Causal Forest methods, which consistently estimate average and heterogeneous causal effects; and SHAP-based explainability analysis, which makes these effects transparent and understandable. This integrated Interpretable Causal Machine Learning framework allows for the assessment of the impact of renewable energy transition on carbon emissions not only quantitatively but also in an interpretable and policy-relevant manner.

3. RESULTS

This study analyzes the causal effect of renewable energy share on per capita CO_2 emissions using machine learning-based causal inference methods with a global panel dataset covering the 1995-2020 period. Based on the causal structure defined by a directed, non-cyclical graph, dual machine learning and causal forest approaches were applied together; mean effects, heterogeneity, and explainable causal mechanisms were evaluated holistically.

The results obtained with the Causal Forest DML model show that a one-unit increase in the share of renewable energy reduces per capita CO_2 emissions by an average of -0.096 (ATE). This finding reveals that renewable energy transition has a causally and statistically significant reducing effect on emissions, even after controlling for economic development, industrial structure, energy intensity, and time effects.

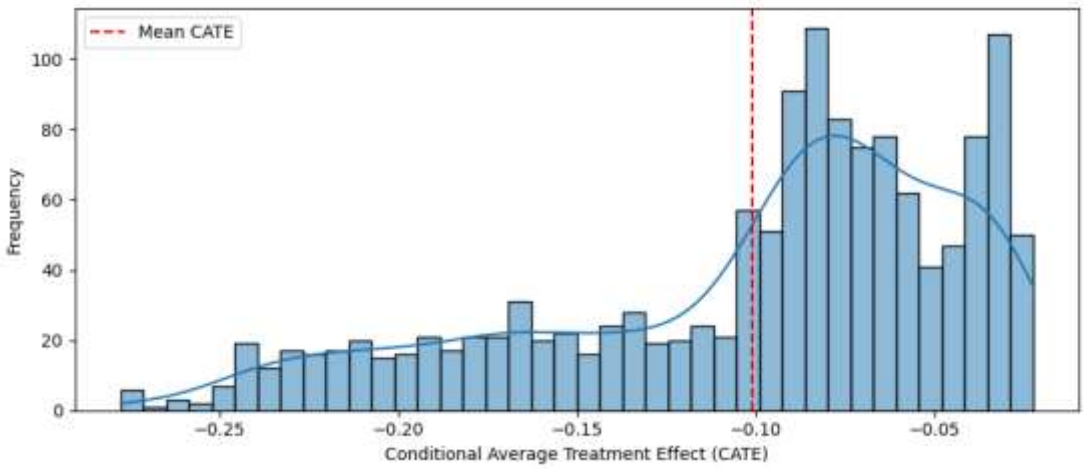

Figure 2: Distribution of conditional average treatment effects (CATE) of renewable energy share on CO_2 emissions

This figure shows the distribution of conditional mean treatment effects (CATE) of renewable energy share on per capita CO_2 emissions. The distribution reveals that the impact of renewable energy transition on emissions is significantly heterogeneous across countries and years. This heterogeneity indicates that the emission reduction effect of renewable energy transition cannot be explained by a single average value and that this effect varies depending on the economic and structural characteristics of the countries. The negative estimated CATE values for all observations show that an increase in renewable energy share does not lead to an increase in emissions under any circumstances. However, the magnitude of the effect varies significantly depending on different structural and economic conditions.

When the distribution of conditional average treatment effects (CATE) is examined, it is seen that the effect is negative for all observations, but the magnitude of the effect differs significantly between countries. While the treatment effect reaches -0.278 under the conditions where the strongest emission reduction is observed, it remains negative at -0.022 even under the weakest conditions. These results show that increasing the share of renewable energy is universally effective in reducing emissions, but the magnitude of this effect is sensitive to country-specific conditions. The mean treatment effect (ATE), shown by the dashed line, confirms that renewable energy transition generally has an emission-reducing effect, while the breadth of the distribution shows that this effect is context-sensitive.

This finding raises a critical policy question: Under what conditions is the renewable energy transition more effective, and what are the underlying mechanisms that determine this heterogeneity? To answer this question, the next step involved a detailed investigation of the determining factors behind heterogeneous causal effects using interpretable causal machine learning methods.

Interpretable causal machine learning analysis reveals the underlying mechanisms behind heterogeneous treatment effects. Figure 3 presents the SHAP summary plot showing which variables shape the predicted causal effects (CATE) of renewable energy share on CO_2 emissions and in what direction. The position of the points on the horizontal axis represents the direction and magnitude of the contribution of the variables to the causal effect, and the colors represent the values of the respective variable from low to high. The global SHAP summary results show that energy intensity is the most dominant factor determining the effectiveness of renewable energy transition. In economies with high energy intensity, the CO_2 emission reduction effect of increased renewable energy share is significantly weaker. In contrast, in countries with low energy intensity and more efficient production structures, this effect is observed to be stronger.

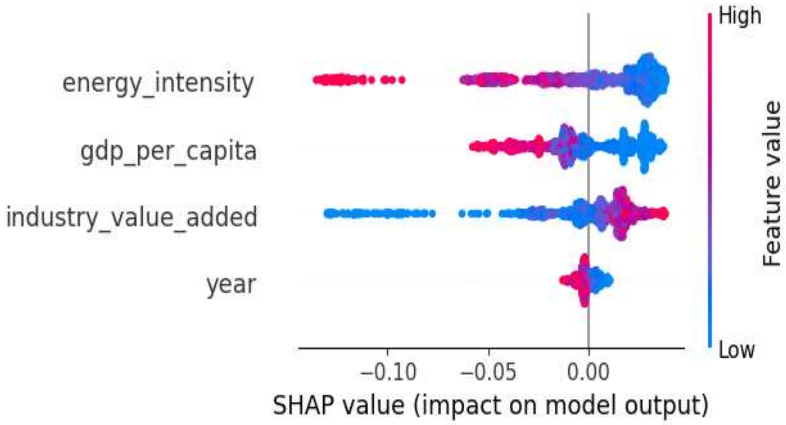

Figure 3: SHAP summary plot explaining the drivers of heterogeneous causal effects on CO_2 emissions

Dependency plots show how the causal effects (CATE) of renewable energy share on CO_2 emissions vary depending on specific structural variables. Energy intensity stands out as one of the most prominent structural factors in explaining the causal effect of renewable energy share on CO_2 emissions. The SHAP dependency plot shown in Figure 4 reveals that the emission-reducing effect of renewable energy transition weakens significantly as energy intensity increases. While an increase in the share of renewable energy strongly and consistently reduces CO_2 emissions in countries with low energy intensity, this effect is observed to decrease significantly, or even become marginal, at high energy intensity levels. This finding suggests that renewable energy investments alone may not be sufficient in economies with low energy efficiency, and that complementary policies aimed at increasing energy efficiency are critical for the effectiveness of emission reduction.

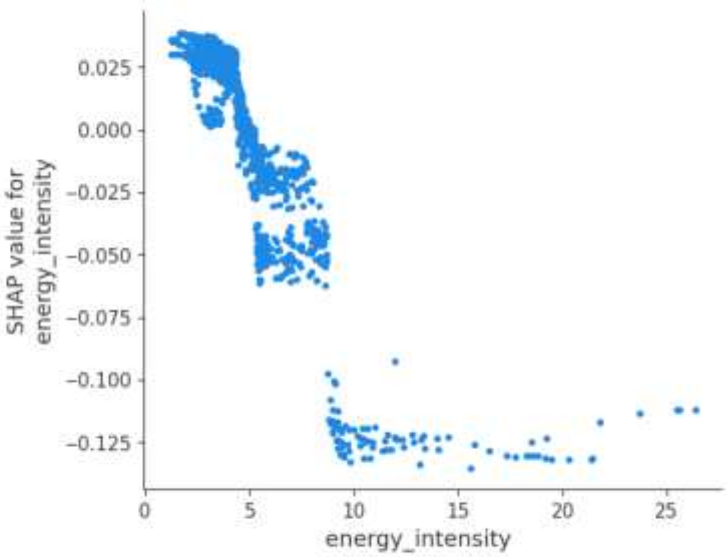

Figure 4: SHAP dependence plot for energy intensity in explaining heterogeneous causal effects on CO_2 emissions

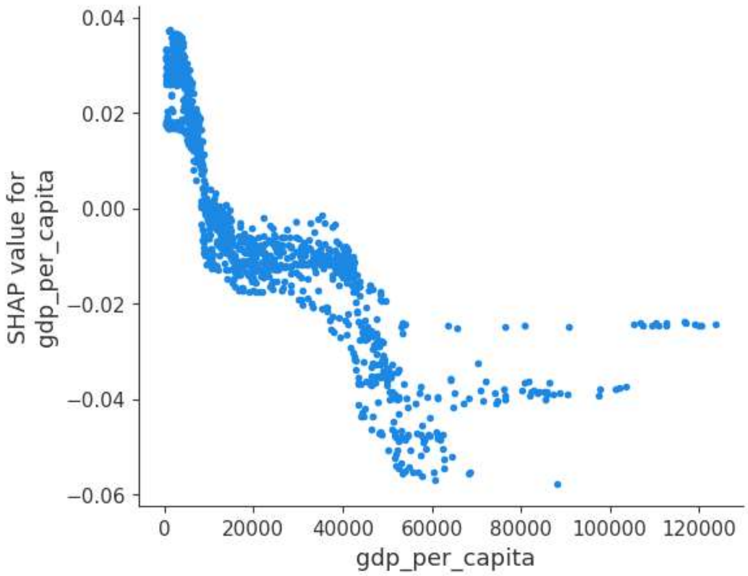

Figure 5: SHAP dependence plot for GDP per capita in explaining heterogeneous causal effects on CO_2 emissions

GDP per capita is another variable that plays an important role in explaining inter-country heterogeneity, but this effect appears to be non-linear. The SHAP Dependence graph shown in Figure 5 illustrates the nonlinear role of per capita income on this causal effect; it reveals that income level strengthens the emission-reducing effect of renewable energy transition, especially in the high-income group, but this effect remains limited in the low and middle-income range. This indicates that below a certain threshold of economic development, structural constraints suppress the income effect.

Figure 6 illustrates how energy intensity and per capita income, when considered together, shape the causal effect of renewable energy share on CO_2 emissions. The SHAP interaction graph reveals that at low energy intensity levels, the emission-reducing effect of renewable energy transition is stronger and more stable, but this effect differs depending on income level. In particular, in high-income countries, an increase in the share of renewable energy combined with low energy intensity significantly reduces CO_2 emissions.

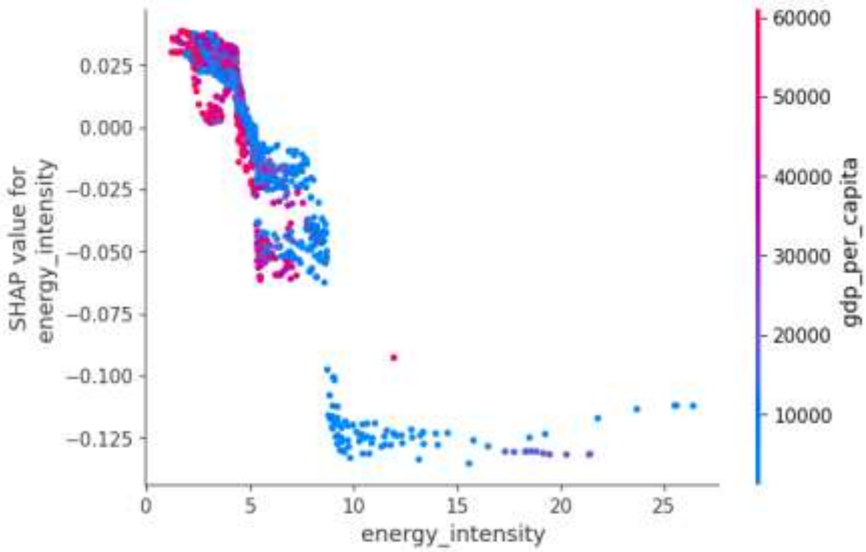

Figure 6: SHAP interaction plot illustrating the joint effect of energy intensity and GDP per capita on the causal impact of renewable energy on CO_2 emissions

Conversely, at high energy intensity levels, even with increased per capita income, the emission-reducing effect of renewable energy transition remains limited. This demonstrates that economic development alone is insufficient; production and consumption structures with low energy efficiency suppress the effectiveness of renewable energy investments. The findings reveal that the impact of renewable energy policies is sensitive to the interaction between energy intensity and economic development, and that complementary policies that increase energy efficiency are critical for achieving sustainable emission reduction.

Figure 7 details how the estimated conditional mean treatment effect (CATE) for Turkey is determined by and in what direction by structural factors, using a SHAP waterfall plot. The findings confirm that the share of renewable energy in Turkey is effective in reducing CO_2 emissions, but show that the magnitude of this effect is limited by industrial structure and economic conditions, especially energy intensity. High energy intensity, in particular, stands out as a dominant factor weakening the emission-reducing effect of the renewable energy transition. In contrast, the contribution of income level and industrial value added is more limited and context-sensitive. This country-specific analysis provides a concrete example of the heterogeneity observed at the global level, revealing that the effectiveness of renewable energy policies is strongly dependent on the structural characteristics of countries. These findings provide an important basis for explaining why the renewable energy transition produces more effective results in some countries, within the scope of the discussion addressed in the next section.

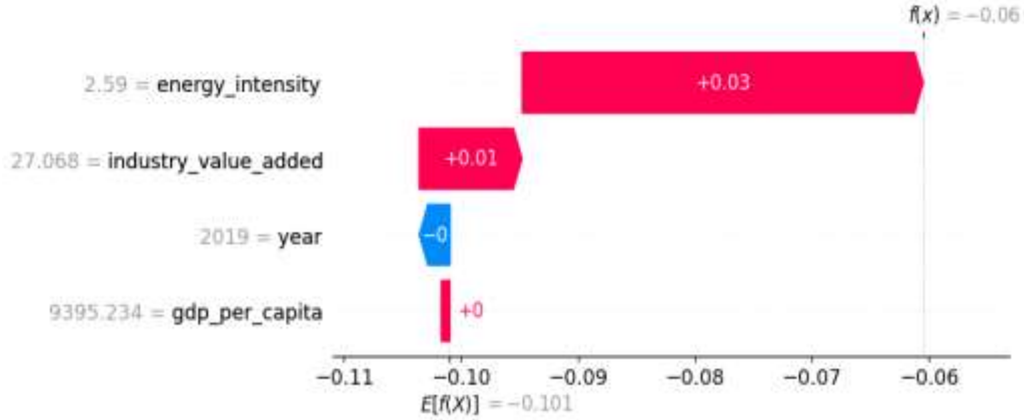

Figure 7: SHAP waterfall plot explaining the causal effect of renewable energy share on CO_2 emissions for Türkiye

4. DISCUSSION

This study provides strong and consistent evidence that an increase in the share of renewable energy causally reduces per capita CO_2 emissions across countries. Findings obtained by going beyond the mean treatment effect show that the magnitude of this effect is significantly heterogeneous between countries and that the effectiveness of renewable energy transitions is highly context-sensitive. The combined use of double machine learning, causal forests, and explainable AI methods reveals not only the existence of this heterogeneity but also the underlying structural mechanisms in an interpretable way.

The consistent negative conditional average treatment effects predicted for all observations demonstrate that an increase in the share of renewable energy does not lead to an increase in emissions under any economic or structural conditions. This finding significantly reduces concerns that renewable energy use might weaken environmental gains through rebound or substitution effects. Therefore, inter-country differences reflect primarily changes in the strength of the causal effect, rather than its direction.

One of the most important conclusions from the interpretable causal analysis is that energy intensity plays a dominant role in determining the effectiveness of renewable energy policies. In economies with high energy intensity, the emission-reducing effect of renewable energy expansion remains systematically weaker. This indicates that in contexts with high energy consumption per unit of economic output, the carbon reduction potential of renewable energy is limited by structural inefficiencies in production and consumption processes. In contrast, in economies with lower energy intensity, the adoption of renewable energy is reflected more directly and strongly in emission reduction. This finding reveals that the effectiveness of the energy transition is inextricably linked to energy efficiency.

The role of income level further reinforces the heterogeneous nature of the causal relationship. While GDP per capita contributes to explaining inter-country differences, this effect appears to be non-linear. Explainable dependence and interaction graphs show that the emission-reducing effect of renewable energy is strengthened, especially in high-income economies, while the income effect remains limited in the low- and middle-income ranges. This suggests that below certain income thresholds, technological constraints, energy efficiency gaps, and sectoral composition dominate the causal mechanism, and that economic growth alone is insufficient to enhance the effectiveness of renewable energy transitions.

Findings regarding industrial structure support this interpretation. In economies with high industrial value added, particularly manufacturing and heavy industry-dominated production structures, the expansion of renewable energy can limit short-term emission reductions. While this does not negate the long-term environmental benefits of renewable energy investments, it points to the necessity of complementary structural transformations to realize their full potential.

The country-specific analysis conducted for Turkey provides a concrete example of how these mechanisms interact in practice. While an increase in the share of renewable energy creates a causal effect in reducing CO_2 emissions, the magnitude of this effect is significantly limited by Turkey's relatively high energy intensity and industry-focused economic structure. Interpretable causal decomposition shows that income level plays a secondary role in this context, while structural and productivity-related factors dominate the causal pathway. This finding underlines that assessments based on average effects may be insufficient for policy design and that country-specific conditions must be taken into account.

These results offer important implications for the design of renewable energy policies. The findings show that renewable energy investments produce the most effective results not in isolation, but when considered together with energy efficiency measures and structural transformation policies. Especially in energy-intensive sectors, policy packages that integrate the use of renewable energy with energy-saving technologies and optimization of production processes can significantly increase the effectiveness of emission reduction. From a management perspective, it is evident that firms should consider renewable energy not as an independent solution, but as part of a broader operational efficiency and decarbonization strategy.

This study presents strong causal and explainable findings, but also has some limitations. The reliance on country-level macroeconomic data limits the direct observation of intra-country regional, sectoral, or firm-level heterogeneities. Furthermore, governance dimensions such as institutional quality, regulatory frameworks, or carbon pricing mechanisms could not be included in the model due to data constraints. In addition, the analysis focuses on concurrent causal effects, excluding lagged or dynamic effects of renewable energy investments.

These limitations, rather than weakening the study's core findings, point to significant opportunities for future research. Analyses with sub-national, sectoral, or firm-level datasets, the use of dynamic causal models, and the comparison of different causal machine learning approaches will contribute to a deeper understanding of the long-term and context-specific impacts of renewable energy transition. In this context, the study offers an early and holistic reference framework integrating interpretable causal machine learning into the empirical analysis of energy and climate policies.

5. CONCLUSION

This study examines the impact of renewable energy share on per capita CO_2 emissions using a combination of machine learning-based causal inference and explainable artificial intelligence methods. Analyses conducted on a global panel dataset covering the period 1995–2020 clearly demonstrate that the renewable energy transition has a causal and systematically mitigating effect on emissions. The average effect findings confirm that energy transition policies are an effective tool in combating climate change.

The study goes beyond average effects, showing that the impact of the renewable energy transition is significantly heterogeneous across countries. The negative conditional average treatment effects for all observations reveal that an increase in the share of renewable energy does not lead to an increase in emissions under any circumstances. However, differences in effect size indicate that the success of the energy transition is strongly dependent on the structural and economic characteristics of countries.

Interpretable causality analysis has revealed the underlying mechanisms behind this heterogeneity. The findings show that energy intensity is one of the most dominant factors determining the effectiveness of the renewable energy transition; Economic development plays a non-linear and threshold-sensitive role. These results indicate that renewable energy policies should not be limited to simply changing the energy supply mix, but should also be considered in conjunction with energy efficiency and transformations in the production structure. The country-specific analysis conducted for Turkey provides a concrete example of this general framework.

Overall, this study goes beyond simply asking whether renewable energy policies "work" or not, revealing under what conditions they are most effective. The interpretable causal machine learning approach, which combines causal inference with explainable machine learning, offers a powerful and transparent analytical framework, both scientifically and policy-wise, for evaluating energy and climate policies. This approach provides a crucial foundation for a new generation of empirical studies that focus not only on the outcomes but also on the causal mechanisms behind those outcomes in sustainability-oriented decision-making processes.

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