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On track but too slow? The dynamics of EU decarbonization

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HIGHLIGHTS

- The study explains EU decarbonization dynamics through integrating circular economy practices, energy transition factors, carbon pricing mechanisms, and digitalization.
- The analysis is carried out using DAG causal discovery, time-varying copula, and support vector regression models.
- Resource productivity acts as a key transmission channel in the system.
- Results unveil strong but evolving dynamic dependency structures with carbon emissions.
- Forecasts indicate a declining trend for carbon trajectories, but the EU fails to meet its 2030 goal.

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ABSTRACT

Despite the strong commitment of European countries to achieve net-zero emissions by 2050, the extent to which key policies and drivers jointly shape emissions dynamics remains insufficiently investigated. The study suggests that the interaction among circular economy, energy transition, emissions trading systems, carbon tax, and digitalization policies creates structural constraints on CO_2 emissions in the European countries. Using annual data from 2000 to 2023, the analysis integrates exploratory causal discovery, time-varying dependence modeling, and machine learning methods to unravel system-level causal structure, dynamic connectedness, and future emission trajectories. The results indicate that resource productivity emerges as a central transmission channel within the system, linking upstream factors (material footprint) and digitalization to downstream emission outcomes. Lagged disequilibrium shocks propagate through resource use as a mediating channel. Time-varying copula models indicate significant heterogeneity and evolving dependence among key factors, highlighting the dynamic nature of policy and relationships over time. Forecasting results, based on a Support Vector Regression model under the European Union's 2030 climate policy framework, indicate a persistently declining emission trajectory, but at a pace insufficient to meet the EU's 2030 target. Sensitivity analysis suggests that this gap does not primarily reflect a policy failure, but the structural limitations in how policy interactions translate into decarbonization outcomes. These findings highlight the need to improve the effectiveness of policy instruments by strengthening resource productivity and accelerating progress toward the targets.

1. Introduction

Human activities have emitted a substantial amount of carbon dioxide (CO_2) and other greenhouse gases (GHG), which has accelerated global warming (Tang et al., 2024; D'Adamo et al., 2023). In response, a number of international initiatives, such as the Paris Agreement and COP28, aim to limit the rise in global average temperature to well below 2°C above pre-industrial levels. These actions meet the Sustainable Development Goals (SDGs) of the United Nations (UN), in particular Goals 7 (Affordable and Clean Energy), 12 (Responsible Consumption and Production), and 13 (Climate Action), which promote a transition toward a more sustainable and low-carbon future (Wang et al., 2024; Salman et al., 2024; Zhang et al., 2015).

The European Union (EU) is among the leading regions to meet a sustainable development agenda, with the objective of achieving net-zero carbon emissions by 2050 and reducing at least 55% by 2030 relative to 1990 levels. Decarbonization cannot be achieved through energy transition or carbon pricing policies alone, it also requires

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improvements in materials productivity across resource-use system. For this purpose, a wide set of policy combinations and technological advancements such as Circular Economy (CE), Energy Transition (ET), Emissions Trading Systems (ETS), and Digitalization (DI) are required (Yao et al., 2024; IPCC, 2018 & 2023; UNFCCC, 2016). CE focuses on resource efficiency, including recycling, material reuse, and sustainable product design, to cut waste and lower emissions. ET aims to shift away from fossil fuels to renewable energy sources like wind, solar, and hydropower, which can make a substantial contribution to the decarbonization of the energy sector. The ETS mechanism is essentially a cap-and-trade market for industries to begin using clean technologies. Each of these strategies is extremely important when it comes to the CO_2 emissions and its efficacy, but their fragmented implementation reduces the potential to fully realize their combined benefits (see, for example, Brink et al., 2016; Sheng et al., 2022; D'Adamo et al., 2023; Tang et al., 2024; Kurniawan et al., 2024; Jamasb et al., 2024; Shobande et al., 2024; Wang et al., 2024; Ayub et al., 2024; Prapaspongsa et al., 2024).

The estimated economic and social costs of climate damages, in the absence of timely and effective strategies, are expected to rise. To mitigate these impacts, achieving net-zero emissions by 2050 is categorized as a central objective of sustainable development (Zhang et al., 2024; Jamasb et al., 2024). Although CE, ET, DI, and ETS are widely recognized as key decarbonization strategies, they are often implemented individually with a lack of their potential interaction in shaping CO_2 emissions. While CE initiatives help to reduce material waste and increase resource efficiency, they lack the energy-oriented strategies that are needed for deep decarbonization (Tian et al., 2023; Jamasb et al., 2024). Similarly, ET promotes the use of renewable energy sources, but it fails in addressing the challenges associated with the sharing and movement of energy and material exchange flows in regional industrial systems (industrial symbiosis). The ETS is a regulatory instrument that provides financial incentives to reduce emissions, but it still needs complementary measures to improve its overall effectiveness (Soliman and Nasir, 2019; Evro et al., 2024). To address these gaps, the integration of CE, ET, ETS, and DI offers significant opportunities for a comprehensive CO_2 emissions strategy. For example, CE practices, which focus on waste reduction through recycling and reuse, can complement ET by reducing the environmental footprint of renewable energy infrastructure (Zhou, 2023; Tian et al., 2023). In addition, ETS, in coordination with CE and ET objectives, will further increase the incentives for sustainable practices. This may help the integration of strategies to maximize resource efficiency and facilitate energy transition in the development of an economic model that achieves carbon neutrality. Moreover, DI and Artificial Intelligence (AI) significantly increase these interdependencies by facilitating real-time data analysis, creating predictive models, and optimizing resource allocation to overcome inefficiencies (Zhang et al., 2023; Tang et al., 2024; Jamasb et al., 2024; Salman et al., 2024).

The scientific problem addresses in this study is that improvement in drivers of decarbonization do not necessarily translate into sufficient absolute carbon reductions. EU decarbonization relies not only on the individual impacts of CE practices, ET, ETS, and DI, but also on how these factors are connected and how their relationships evolve over time (Geels, 2012; Errendal et al., 2023; Evro et al., 2024; Tang et al., 2024). As a result, a declining emission trajectory alone does not indicate whether the EU is progressing at the speed demanded to meet its 2030 climate target (Tang et al., 2024; Bibri et al., 2024). Therefore, it is important to examine the system-level links, dynamic dependencies, and transmission channels that explain how these factors together shaping CO_2 emission pathways and the gap between projected emissions and the policy target. Accordingly, this study has linked the topic "on track but too slow" to two empirical meanings. To indicate that EU decarbonization is on track, a declining projected emissions trajectory is indicated. Whereas, to evaluate whether its pace is sufficient, projected emissions is compared with the 2030 target. The fundamental part, causal and dependency analysis, helps to identify the system-level pathways associated with the projected trajectory.

Research on CO_2 emissions has predominantly examined the impact of various indicators, such as digitalization (e.g. Shi et al., 2024; Cui et al., 2024; Cao et al., 2024; Li et al., 2024; Ayub et al., 2024; Maftei et al., 2025), energy transition (see Tian et al., 2023; Li et al., 2024; Salman et al., 2024; Shobande et al., 2024), carbon tax (e.g., Lu et al., 2025a; Lu et al., 2025b; Li et al., 2024), material efficiency (Sen et al., 2021), emission trading system (see Stavins, 2007; Tang et al., 2024; Shobande et al., 2024; Zhang et al., 2024), municipal waste (refer to Ghisellini et al., 2016; Wang et al., 2024; Prapaspongsa et al., 2024; Deng et al., 2025), energy efficiency (e.g. Zhou and Ji, 2021; Zhang et al., 2024), resource productivity (e.g. Mushafiq and Prusak, 2023; Li et al., 2024), and renewable energy consumption (Abrell and Weigt, 2008; Zhou, 2023; Li et al., 2024). Despite the growing enthusiasm for CO_2 emissions, these strands of research have largely developed in parallel, and limited evidence exists on how these mechanisms interact as an integrated system shaping emissions dynamics. Based on this gap, this study investigates the causal structure, the time-varying connectedness, and the transmission channels among DI, ET, ETS, CE, and CO_2 emissions. Additionally, the analysis examines whether their interaction strengthens CO_2 emissions outcomes. Specifically, the study addresses the following key questions:

1) What is the plausible causal structure among DI, ET, ETS, and CE practices? Engaging with this question unveils the causality mechanisms among these factors and helps in understanding the pathway of these strategies on CO_2 emissions. Moreover, it unveils the factor acting as a transmission channel driving emission changes.
2) How does the connectedness among these mechanisms evolve over time? This question answers how the nature of time-varying connectedness among the linked strategies evolves over time and how strongly they are connected.
3) Is the projected carbon emissions trajectory sufficient to meet the climate goals by 2030 in the EU area, and which system-level factors may explain any remaining policy gap? The main goal of this question is to provide indicative CO_2 emissions projections. This question offers valuable insights to foster the achievement of the EU's 2030 target for climate change.

Through addressing these questions, the study contributes to the environmental economics literature in four ways. To the best of our knowledge, the study is among the first to examine the interactions within the policy-technology-resource system (system-level policy interaction) involving ET, ETS, DI, CE, and CO_2 emissions in the EU context. The study provides a dynamic perspective on CO_2 emissions by identifying resource productivity as a central transmission channel through evaluating how the dynamic relationships among the factors affect emissions over time. This insight provides forward-thinking policymaking and anticipates future challenges and opportunities in CO_2 emissions targets in the EU. Additionally, the study combines Directed Acyclic Graph based causal discovery, time-varying Copula models, and Support Vector Regression to analyze causal structure, dynamic dependences, and emissions forecasting under 2030 climate policy targets, and sensitivity analysis to key decarbonization drivers. Further, the study considers several key control factors, such as material footprint, resource productivity, and municipal waste generation (representing upstream, midstream, and downstream circular economy activities), to reduce potential bias. Ultimately, to address policy stringency and cross-country heterogeneity, the analysis considers both national carbon taxes and emission trading systems, as well as the EU-ETS.

This article is organized into six sections. The introduction (Section 1) outlines the research problem, research motivation, research questions, and key contributions. The literature review (Section 2) looks at theoretical background and existing studies on the impact of DI, ET, ETS, and CE practices on CO_2 emissions, highlighting their key gaps and opportunities. Section 3 outlines the methodological framework. Section

4 illustrates the variable definitions and the data sources used in the analysis. In Section 5 the empirical findings and some robustness checks are presented and discussed. Lastly, in Section 6 the main findings are summarized, significant policy recommendations are proposed, and the study's limitations and future research agenda are mentioned.

2. Literature review

2.1. Theoretical background

The study relies on four key pillars to establish a foundation for analyzing the joint role of CE, ET, ETS, and DI in addressing the CO_2 emissions challenges. The first aspect of the work draws on the circular economy theory, which underscores the notable role of resource efficiency, material reuse, waste management, and lifecycle optimization to reduce waste and, consequently, carbon emissions (Ghisellini et al., 2016). Second, the energy transition perspective emphasizes the need for an immediate shift from high-carbon to low-carbon economies through the adoption of renewable energy, facilitating the adoption of more accessible green technologies and supportive policies (Geels, 2012). Third, as suggested by Stavins (2007), the role of market-based principles, especially the one related to the ETS, is considered in establishing carbon reduction policies through offering financial incentives and encouraging innovative concepts. Additionally, the principle of digital transformation underscores resource flow optimization and may strengthen emission reduction regulations (Bibri et al., 2024). These perspectives provide a comprehensive framework for studying the trade-offs and interactions among CE, ET, ETS, and DI approaches.

2.2. Circular economy

Numerous studies have emphasized the role of circular economy strategies and practices in reducing carbon emissions. Sen et al. (2021) and Tian et al. (2023) analyze how circular economy and material efficiency strategies can accelerate decarbonization and support net-zero targets. Using GHG emissions as a case study, Mushafiq and Prusak (2023) and Kurniawan et al. (2023) explore how digital waste management systems, resource productivity, and material footprint are associated to emissions in the EU-27. Wang et al. (2024) examine whether circular economy practices and green logistics reduce carbon emissions in the EU and how waste generation and economic growth affect this relationship. Prapaspongsa et al. (2024) assess global life-cycle GHG emissions from municipal waste management and evaluate the role of circular economy practices in achieving carbon neutrality. Jamasb et al. (2024) evaluate whether economic growth can be achieved without environmental externalities through circular economy practices. More recently, Deng et al. (2025) investigate how China's Zero-Waste City program affects emissions and what drives the emissions. Generally, the studies have focused on particular applications of CE practices, rather than a thorough analysis of CE's contribution to CO_2 emissions.

2.3. Energy transition

To understand how decarbonization initiatives are shaped through energy transition and its integration with other strategies, some scholars have studied the role of green energy on pollutant emissions across countries. Chen et al. (2021) examine the material intensity of renewable energy technologies and emphasize their circular design potential. Zhou (2023) reviews the worldwide carbon neutrality transition through energy efficiency, renewable carbon trading, and advanced energy policies. More recently, several studies have analyzed the impact of ET on carbon-neutrality programs in specific country groups. For instance, the impact of the ETS and the energy transition on carbon intensity in OECD countries is investigated by Shobande et al. (2024). Li (2024) studies the effects of digital transformation, eco-efficiency, natural resource extraction, and energy transition on carbon outputs and environmental quality for G-15 countries. Elsewhere, Li et al. (2024) examine the impact of renewable energy, green taxes, and trade openness on carbon targets in BRICS nations. Wang et al. (2024) emphasize how hybrid systems, especially in developing countries, could potentially be leveraged for renewable energy. On another front, Yao et al. (2024) examine the role of energy-efficiency measures in achieving CO_2 emissions by highlighting cost-effective ways to decarbonize electricity grids. Still, few studies have looked closely at how energy transition integrates with CE practices and digitalization.

2.4. Emissions trading system

Several years ago, Stavins (2007) discussed a comprehensive US-ETS capable of addressing global climate change, especially when combined with international linkage. Later, Fang et al. (2021), and Wen et al. (2023) argue about China's ETS and how different carbon allowance allocation rules affect emission reduction and intensity at minimum cost. Errendal et al. (2023) study carbon pricing's contribution to the net-zero GHG emissions pathway, when combined with complementary policies in order to investigate the potential role of carbon pricing in transforming the pathway toward net-zero emissions. Also, Li et al. (2024) confirm that green taxes enhance carbon neutrality in BRICS countries. In another study, Zhang et al. (2024) compare the effectiveness of carbon tax and ETS in reducing GHG emissions. To evaluate how the EU-ETS contributes to the SDGs, Foggia et al. (2024) explore the interaction between European installations covered by ETS and the various sustainable development variables. More recently, Lu et al. (2025a) support the joint effects of ETS and carbon tax on emission reduction in the building sector from an embodied-carbon perspective. In another study, Lu et al. (2025b) discuss that the combination of ETS and a differentiated carbon tax performs better than combining ETS with a uniform carbon tax in the construction sector. Although ETS mechanisms are well-studied in terms of economics and design, their combined effects with CE and DI on carbon emissions across various regions remain unexplored.

2.5. Digitalization

To understand the role of digitalization on environmental degradation, several scholars have analyzed both the direct and indirect effects of internet usage, AI, Internet of Things (IoT), etc. on pollutant emissions. Recently, some scholars have focused on the role of digital cities and economies in emission reduction. Yang et al. (2022), Cao et al. (2024), Shi et al. (2024), and Wang et al. (2024) evaluate how digital technology and the digital economy affect China's carbon emission reduction. Moreover, Ayub et al. (2024) examine the relationship between digital economy development and carbon emissions for BRICS countries. In another study, Li (2024) highlights the leading role of the digital transformation effect on environmental sustainability, especially carbon reduction, in the G-15 countries. In a similar case study, aiming to investigate the role of digitalization on net-zero carbon programs, Yao et al. (2024) address the role of industrial robot adoption on carbon emissions. Overall, to overcome barriers such as data accessibility and technology adoption, the literature suggests that digitalization should be integrated with CE and ET strategies.

2.6. Multiple interactions

Recent research has stressed the need to analyze the effects of CE, ET, ETS, and DI factors on CO_2 emissions, particularly by investigating their interactions and trade-offs. Recently, Errendal et al. (2023) discuss the effective role of complementary policies alongside carbon pricing in the net-zero pathway. The extent to which the EU-ETS integration with digitalization, renewable energy usage, and circular economy practices improves carbon reduction is documented in D'Adamo et al. (2023).

Both individual and joint effects of energy transition and pollution control policies on carbon reduction mainly depend on policy combinations in China (Tang et al., 2024). As a comparative study, Evro et al. (2024) review carbon reduction strategies and policy interactions adopted by the US, the EU, and China. A systematic analysis of smart cities in the work by Bibri et al. (2024) unveils the integration of AI, IoT, and resource efficiency on carbon emissions. For the case of European countries, Maftei et al. (2025) highlight the crucial direct impacts of mixed green digitalization and renewable energy on GHG emissions. Despite these advancements, a comprehensive framework capturing these multi-dimensional interactions is still lacking in the literature, especially for Europe.

This literature shows a shift from isolated policy evaluation toward the analysis of policy interconnections. Nevertheless, the main gap still remained. First, several studies (e.g., Tian et al., 2023; Shobande et al., 2024; Li, 2024; Mushafiq and Prusak, 2023) have mainly focused on an individual mechanism, such as energy transition, carbon pricing, circular economy, or digitalization, rather than their joint actions within a unified system. Second, some studies (see D'Adamo et al., 2023; Tang et al., 2024; Evro et al., 2024) consider policy interactions often conducted in static and linear frameworks, which reduce their ability to capture the dependencies evolution and changing relationships over time. Third, relatively limited attention has been dedicated to the joint effects and transmission channels on emissions. These gaps justify the need to conduct an integrated framework that involves causality patterns, dynamic dependencies, and their joint effects on emission trajectories within the same empirical context.

2.7. Methodological comparative analysis

Most of the existing literature examining the impacts of CE, ET, ETS, and DI on CO_2 emissions (see Table A-1 in the Appendix) employs a wide range of econometric models and optimization frameworks, often difficult to compare. While some recent studies consider policy complementarities, most of the analysis focuses on individual relationships or single methodological approaches. Despite their valuable insights, these different methodological approaches often fail to integrate, leaving gaps in understanding strategy interactions. Although some works acknowledge policy interactions, the empirical analysis often remains limited to linear specifications or static frameworks. Additionally, contemporaneous causality structures, causal transmissions pathways, and dynamic dependences remain unexplored, which is problematic especially within an integrated framework such as the EU system. Apart from these gaps, forecasting exercises are rarely targeted and linked to policy interactions and interactions. To fill these gaps, the study contributes to the literature by combining causal discovery, copula-based dependence modeling, and machine learning forecasting to analyze interactions, evolutions, and predictions within a system-level framework. Moreover, this comprehensive approach addresses the gap between isolated policy evaluation and comprehensive decarbonization analysis.

2.8. Contributions of the study

In this study, critical gaps in understanding CE, ET, ETS, and DI are addressed by moving toward a system-level perspective. The existing literature is strengthened by our key contributions: 1) The study analyzes how CE, ET, ETS, and DI interact individually and jointly to reduce carbon emissions within an integrated EU framework and how their joint effects impact CO_2 emissions outcomes. 2) A combination of advanced methodologies allows us to understand the multiple contemporaneous causal links, dynamic connectedness evolution, and forecast future emission trends related to CE, ET, ETS, and DI policies. 3) The study connects policy interaction analysis to emission projections under the Paris Agreement to assess the progress toward the EU's 2030 carbon target. 4) By considering carbon policy heterogeneity, national and EU-ETS systems and carbon taxes across EU member states, the study offers targeted insights for EU climate strategy design.

3. Methodology

The methodological framework follows a sequential system-level logic. This integrated and comprehensive methodological framework is, first, the Directed Acyclic Graph (DAG), in particular the Fast Adjacency Skewness (FASK) algorithm, which identifies the plausible causal structure among CE, ETS, ET, and DI, and their pathways shaping emissions within the EU context. Second, to measure how these relationships connected strongly and how they evolve over time, time-varying copula models are applied. Third, to determine whether this system-level pathways is sufficient to meet the EU's 2030 target, Support Vector Regression (SVR) is conducted to forecast indicative emissions trajectories under the EU 2030 policy framework. [1] More specifically, to assess whether these connections and dynamic interactions are sufficient to achieve the EU's 2030 decarbonization goal (approx. 63 Mt), sensitivity analysis is carried out.

In this way, the methodological framework connects causal identification, dynamic dependence analysis, and forecasting trajectories within a system-level empirical structure. This combination further addresses the limitations of modeling linear relationships, dynamic interdependencies, and structural inter-channel transmission, and it allows us to move beyond the linear and static framework. The proposed methods jointly provide an in-depth analysis of the interactions and transmission channels shaping emissions trends through the integration of causal relations, dynamic dependencies, and prediction within a unified framework.

3.1. Directed Acyclic Graphs and the Fast Adjacency Skewness algorithm

Directed Acyclic Graphs (DAG) are suitable for multiple contemporaneous causality analyses. A graphical model derived from probability data was developed by Pearl in the 1990s to systematically suggest and represent causal relationships. DAG and its algorithms identify direct, indirect, and spurious relationships through the use of conditional independence tests. Furthermore, the DAG approach has the ability to model latent or unknown factors and further consider them for analyzing complex interactions in a system (Pearl, 2000; Zhang et al., 2019). In this study, to explore the plausible multiple contemporaneous causal relationships of CE, ET, ETS, and DI factors and their leading role on CO_2 emissions, DAG is employed. The implementation of DAG algorithms in this study facilitates a systematic understanding of the dynamic interplays among CE, ET, ETS, DI, and CO_2 emissions, addressing gaps in traditional econometric analyses. More specifically, a DAG algorithm identifies causality direction based on a conditional dependence test and visual graphs that include nodes and edges. Nodes refer to factors, and edges represent possible causal links. By using conditional independence tests, which are usually based on partial correlation and mutual information, two variables are determined to be independent based on a set of other variables. For refining the final graph, a method is proposed that removes the edge between the nodes if independence is resulted through the separation criterion, inferring that non-causal links are omitted (Pearl, 2000; Spirtes et al., 2000; Demiralp and Hoover, 2003).

Among the search algorithms based on graph theory, this paper employs the Fast Adjacency Skewness (FASK) method, which uses a non-Gaussian (skewed) distributional metric to determine causation

[1] Given that the study relies on aggregated annual frequency of the data, the DAG/FASK, copula, and forecasting estimates are interpreted as plausible causal patterns, dynamic dependencies, and indicative emissions trajectories within the EU decarbonization system. To address the limitation of dealing with aggregated data, the study conducted a complementary robustness check with country-level panel estimations.

directions. Compared to conventional correlation- or lag-based methods, FASK first determines undirected adjacencies via conditional independence tests and subsequently suggests direction via asymmetry (skewness). Since the algorithm uses distributional asymmetries to map causal edges, its results may be sensitive to limited sample size. In this case, the FASK result are interpreted as plausible causal patterns. Nevertheless, a key strength of the algorithm is its ability to identify both feedforward and feedback (2-cycle) structures that are prevalent in complex policy-technology systems. By leveraging higher-order statistical moments, FASK is able to improve orientation in systems that exhibit contemporaneous and potentially cyclic interactions (Rawls et al., 2023). This makes the FASK algorithm particularly suitable to model the system relationships among CE, ET, ETS, DI and CO_2 emissions.

The FASK algorithm proceeds in two main steps. First, it estimates the undirected skeleton of the graph using a constraint-based procedure (e.g. FAS), which relies on conditional independence tests to suggest adjacencies. In the second step, each adjacency X−Y is oriented by exploiting asymmetries in the data distribution. The algorithm first tests whether the edge corresponds to a 2-cycle by assessing whether the differences between corr(X,Y) and corr(X,Y|X > 0), and between corr(X, Y) and corr(X,Y|Y > 0) are both significantly different from zero. If so, a bidirectional edge X↔Y is inferred. Otherwise, the direction is determined using the left-right orientation rule, which leverages differences in conditional expectations induced by skewness to decide whether X→Y or Y→X (Sanchez-Romero et al., 2019). In this study, the long-run and short-run causal patterns are distinguished by incorporating a one-period lagged error-correction term ($lECT_{t-1}$), derived from the Johansen analysis, into the system-level framework. This specification follows the conventional ECT framework and allows the system to adjust in response to disequilibrium observed in the previous period (Engle and Granger, 1987; Johansen, 1991; Lütkepohl, 2005).

3.2. Time-varying copulas

Sklar (1959) developed copulas as mathematical functions to link univariate marginal distributions with full multivariate distributions. Using copulas, bivariate and multiple dependencies can be modeled in a flexible manner, assuming nonlinear, asymmetric, and tail dependencies. These features make copulas particularly useful for measuring correlation among multiple variables, unlike traditional correlation tests, in fields like finance, environmental studies, and energy (Zhou and Ji, 2021; Tan et al., 2022; Pakrooh and Manera, 2024). Based on Patton (2006), copula functions overcome these limitations by decoupling marginal distributions from the dependence structure, which allows for more accuracy in modelling nonlinear and time-varying relationships. To illustrate this concept, consider a two-dimensional distribution function $H(x_1, x_2)$ and its marginal distributions $F_1(x_1)$ and $F_2(x_2)$. Then, the copula function C(.) is formulated as:

$$H(x_1, x_2) = C(F_1(x_1), F_2(x_2)) \tag{1}$$

In order to analyze the degree of connectedness among CE, ET, ETS, DI, and CO_2 emissions, how their connectedness evolves over time, and which factor drives CO_2 emissions, we adopt time-varying copulas, which capture the evolution of relationships over time, and incorporate the dynamic adjustment to the dependency structure. The dynamic factor is critical to analyze phenomena such as carbon reduction due to changes in policy implementations and technological advancement. Time-varying copulas are classified into two main groups, Archimedean copulas and Elliptical copulas, and many families, such as Gaussian, t-student, Gumbel, Clayton, Joe, and survival forms (Masseran and Hussain, 2020; Zhou and Ji, 2021; Soliman and Nasir, 2019):

1) Elliptical copulas, including Gaussian and t-copulas, assume symmetric dependency structures. Generally, the Gaussian copula is used as a baseline, since it is indicated to model linear relations, although it has less flexibility in capturing tail dependencies. In contrast, t-copula incorporates heavy tails, so it is ideal for modeling extreme co-movements (Patton, 2006; Masseran and Hussain, 2020).
2) Archimedean copulas, such as Gumbel, Clayton, and survival forms, are more flexible for modeling asymmetric dependencies. Among all, particularly the Survival Joe-Clayton copula (SJC) is developed to describe the behavior of the dependence structure not only in the upper tail for extreme negative values but also in the lower tail for extreme positive values of variables (Zhou and Ji, 2021; Tan et al., 2022). The SJC copula can be written as:

$$C_{SJC}(u, v|\tau^U, \tau^L) = 0.5\left[C_{JC}(u, v|\tau^U, \tau^L) + C_{JC}(1-u, 1-v|\tau^U, \tau^L) + u + v - 1\right] \tag{2}$$

$$\tau_t^{\frac{U}{L}} = \widetilde{\lambda}\left(\omega^{\frac{U}{L}} + \beta^{\frac{U}{L}}\tau_{t-1}^{\frac{U}{L}} + \alpha^{\frac{U}{L}}\frac{\sum_{i=1}^{10}|u_{1,t-i} - u_{2,t-i}|}{10}\right) \tag{3}$$

where the terms τ^U *and* τ^L are the upper and lower tail dependencies and C_{JC} indicates the classical Joe-Clayton (JC) copula, which cannot assess the behaviors of both tails simultaneously. Therefore, the SJC copula (2) is used to overcome the limitations of the JC copula. To incorporate the time-varying properties, Patton (2006) proposes the use of evolution parameters in the SJC copula (see equation (3)), where $\widetilde{\lambda}$ is the logistic transformation ensuring that the dependence parameter $\tau^{U/L}$ is in the range of (0,1). The SJC copula represented in equation (3) follows an Auto-Regressive Moving-Average (ARMA) process of order (1,10). $\beta^{\frac{U}{L}}\tau_{t-1}^{\frac{U}{L}}$ is the autoregressive term, $\frac{\sum_{i=1}^{10}|u_{1,t-i}-u_{2,t-i}|}{10}$ represents the persistence effect and variation in dependence, while $\alpha^{\frac{U}{L}}$ is the forcing value.

3.3. Support vector regression

The ability to account for complexity, nonlinearity, and high dimensionality makes Machine Learning (ML) a valuable tool for forecasting in environmental applications. Among these approaches, Support Vector Machines (SVM) and their regression extension, Support Vector Regression (SVR), are widely used due to their robustness and strong performance in modeling nonlinear relationships (Smola and Schölkopf, 2003; Bishop, 2006; Li, 2022; Wang et al., 2024).

Originally developed for classification (Cortes and Vapnik, 1995), SVM has been successfully extended to regression settings. The effectiveness of SVR in capturing nonlinear dynamics and achieving low prediction errors largely depends on the use of kernel functions (Smola and Schölkopf, 2003; Pakrooh and Pishbahar, 2019). Previous studies have demonstrated its applicability in forecasting carbon emissions, energy consumption, and related macroeconomic variables (e.g., Li, 2022; Wang et al., 2024).

In addition, combining SVR with other machine learning techniques or with time-series models (e.g., ARMA) in hybrid frameworks has been shown to further improve forecasting accuracy by exploiting complementary strengths (Oliveira and Ludermir, 2014; Pokora, 2017; Pakrooh and Pishbahar, 2019; Saha et al., 2021; Qin et al., 2023).

Technically, SVR maps input data into a higher-dimensional feature space through a nonlinear transformation, where a kernel function defines the relationship between inputs and outputs:

$$f(x) = \omega^T\phi(x) + b \tag{4}$$

where ω and b denote the weight column vector and intercept, respectively. SVR employs an ε -insensitive loss function, allowing deviations from observed values within a predefined threshold ε.

A flat function is obtained by minimizing the norm of ω, which leads to a convex optimization problem:

$$\begin{aligned} &min\ \frac{1}{2}\ \|\omega\|^2 \\ &s.\ t. \begin{cases} f\ (x_i) - y_i \le \varepsilon \\ y_i - f\ (x_i) \le \varepsilon \end{cases} \end{aligned} \tag{5}$$

The predicted value is denoted by $\hat{y_i}$. This formulation assumes the existence of a function that approximates the data within an acceptable ε-level of accuracy. To account for larger deviations, slack variables ξ_i and ξ^*_i are introduced to measure under- and overestimation relative to the ε-tube. The resulting objective function is given by:

$$\begin{aligned} &min\ \frac{1}{2}\ \|\omega\|^2 + C\sum_{i=1}^{N}(\zeta_i + \zeta_i^*) \\ &s.\ t. \begin{cases} y_i - \omega^T\phi(x_i) - b \le \varepsilon + \zeta_i \\ \omega^T\phi(x_i) + b - y_i \le \varepsilon + \zeta_i^* \\ \zeta_i, \zeta_i^* \ge 0 \end{cases} \end{aligned} \tag{6}$$

where C is a penalty parameter controlling the trade-off between model complexity and prediction error (Sharifian and Barati, 2015; Abbasimehr and Baghery, 2022).

In this study, an SVR-based model is used to generate indicative[2] carbon emission projections in line with the EU's 2030 climate targets, which requires at least a 55% reduction relative to the baseline year (1990). The target value is then compared with the SVR-based 2030 forecast to assess whether the projected emission pathway is consistent with the EU's 2030 climate objective. The forecasted 2030 emission value is obtained from the selected SVR models using the targeted explanatory variables. The corresponding 2030 target emission level is quantified as 45% of the 1990 baseline CO_2 emissions, satisfying the EU's objective of a 55% reduction relative to 1990 levels. Based on the baseline emission level, the target value is approximately 63 Mt. The policy gap is calculated as the difference between the SVR-forecasted 2030 CO_2 emissions and the 2030 target emission level.

More specifically, the alignment with the Paris Agreement's objectives includes limiting global warming to below 2 degrees Celsius, achieving a 47.5% increase in municipal waste recycling, a 30% increase in resource productivity, a 62% reduction in emissions through the ETS, a 42.5% increase in the share of renewable energy in the energy mix, and a 20% reduction in emissions through digitalization and technological advancements under the EU's 2030 carbon target.[3] The Lagrangian dual formulation of the SVR model (see equation (7)) is adopted to obtain robust projections and to assess the role of key drivers in shaping emission trajectories.

$$CO_2(t) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\ \mathrm{K}\ (x_i, x_t) + b \tag{7}$$

where α_i and α^*_i are Lagrange multipliers, x_t denotes the vector of explanatory variables, and $K(\cdot)$ is the kernel function capturing nonlinear relationships.

4. Data and variable definition

The empirical study aims to examine how ETS, CE, ET, and DI affect CO_2 emissions. Time series spanning the period 2000-2023 (annual data, T = 24) for the European countries (cross-sectionally aggregated over 27 European countries participating in the EU carbon-pricing framework, N = 27) are used in this study.[4&5] The key explanatory variable is annual emissions. The factors that identify energy transition are energy intensity and renewable energy shares; for the carbon policy index, both national and the EU-level emission trading system and also carbon taxes are considered. In terms of circular economy practices, all upstream, midstream, and downstream actions, including material footprint, resource productivity, and municipal waste recycling practices, are accounted for. For digitalization, internet penetration rate as a backbone of the digital economy is selected. All the information for the considered variables comes from the reliable and credible databases, including Eurostat, WorldBank, and Our World in Data. The variables are described in more detail with their used sources in Table 1.[6]

Table 1
Variables description.

Variables		Symbol	Measurement	Source
Carbon Emissions	Annual CO_2 emissions	CO_2	Metric tons	Our World in Data
Energy Transition	Energy Intensity	EI	The index is constructed based on GDP (constant 2015 US$) and primary energy consumption (TWh) in metric TWh/$	World Bank Indicators
	Renewables	RE	% of total primary energy consumption	Eurostat
Climate policy	Carbon Policy Index	CPI	The index is constructed based on national carbon taxes, national ETS schemes, and EU-ETS prices.	World Bank Carbon Pricing Dashboard
Circular Economy	Material Footprint	MF	Demand for material extractions measured in metric tons	Eurostat
	Resource Productivity	RP	Output per unit of domestic material consumption measured in euro/kg	Eurostat
	Municipal Waste	MW	Recycled waste in metric tons	Eurostat
Digitalization	Internet Usage	IPR	Individuals using internet (% of the population)	World Bank Indicators
Regime control	Post-2004 indicator	D	Dummy variable, equal to 0 before 2004 and 1 from 2004 onward	Authors' construction

[2] Given the limited sample size, the SVR-based forecasting values are interpreted as indicative trajectories, rather than precise long-term predictions.

[3] Further details on the European Commission's 2030 targets can be found on the official website: https://commission.europa.eu/topics/climate-action/eu-climate-energy-and-environmental-targets/2030-targets_en.

[4] The N = 27 included countries are: Austria; Belgium; Bulgaria; Croatia; Cyprus; Czechia; Denmark; Estonia; Finland; France; Germany; Greece; Hungary; Italy; Latvia; Lithuania; Luxembourg; Netherlands; Norway; Poland; Portugal; Romania; Slovakia; Slovenia; Spain; Sweden; Switzerland. Although Norway and Switzerland are not EU member states, they are included in the sample, because both countries participate in the EU-ETS, making them integral to the European carbon market and directly exposed to the same carbon pricing framework as EU member states (European Commission, 2023).

[5] Since the main objective of the study is to analyze system-level EU decarbonization dynamics, the annual aggregated series are used to examine EU-level causal links, dynamic dependence, and emission trajectories over time. However, aggregation may reduce cross-country heterogeneity, the complementary country-level panel robustness checks are conducted and reported in the Appendix.

[6] For source link, refer to the Appendix, Table A-2.

The dependent variable is annual emissions (CO_2), which quantifies environmental damage measured in metric tons. Among other air pollution indicators, carbon emissions are particularly problematic due to their long life in the environment and global impact (Li, 2024).

Energy use is the driving cause of declining environmental quality across the world. Two variables, representing energy transition factors, are energy intensity and renewable energy share in the energy mix (Yang et al., 2022). Energy intensity (EI), which measures the amount of energy consumed per unit of economic output, serves as a key component of national economies and plays a significant role as a provider to many sectors and in decarbonization goals (Dechezleprêtre et al., 2025). Renewable energy sources have multiple environmental advantages over fossil fuels, such as accelerating the energy transition, reducing carbon emissions, and mitigating climate change. The EU Renewable Energy Directive program raises the binding target for 2030 from 32% to a minimum of 42.5% share of renewables in the EU's energy mix (EEA, 2025). Therefore, this study takes into account the percentage of renewable energy (RE) as a second energy transition proxy.

Climate policies, such as carbon taxes and emissions trading systems (ETS), have proven to be effective and stringent tools for improving environmental quality. Strong policy commitments—ranging from national ETS schemes to higher carbon taxes—provide incentives for investment in the expansion and development of low-carbon technologies. In general, higher carbon taxes and ETS permit prices significantly reduce carbon emissions (Kohlscheen et al., 2024). Recent studies (Lu et al., 2025a, 2025b) show that ETS and carbon taxes can operate as complementary carbon-pricing instruments. Therefore, in this paper, the carbon policy index (CPI) is constructed based on national carbon taxes (including the Denmark carbon tax, Estonia carbon tax, Finland carbon tax, France carbon tax, Latvia carbon tax, Luxembourg carbon tax, Netherlands carbon tax, Norway carbon tax, Poland carbon tax, Portugal carbon tax, Slovenia carbon tax, Spain carbon tax, Sweden carbon tax, and the Switzerland carbon tax in metrics euro), national ETS schemes (e.g., Switzerland ETS, Germany ETS in metrics euro), and the EU-ETS price series collected from the World Bank Carbon Pricing Dashboard. Indeed, the approach combines national carbon taxes, national ETS prices, and the EU-ETS allowance price. Therefore, the CPI is not intended to imply that these variables are economically equivalent, instead, it captures the shared movement of carbon-pricing instruments, which provides a system-level proxy for the common variations in the carbon-policy stringency across the European carbon market. Since these policies differ in level and unit, all prices are converted to euros, harmonized at an annual frequency, the series are standardized using Z-score, and lastly, Principal Component Analysis (PCA) is applied to capture the largest share of common variations across the standardized series.[7] The first PC (PC1) captures the largest individual share of common variation. It has an eigenvalue of 1.313 which explains 43.77% of the total variation. The component weights are 0.5781 for the national ETS, 0.5285 for the EU-ETS, and 0.6216 for the national carbon-tax component.[8] As a robustness check, ETS prices and national carbon taxes are also examined separately to assess whether the results depend on combining the two instruments (see Table A-11 of the Appendix). In addition to this, an alternative equal-weighted carbon Policy Index, CPI^{ALT}, is constructed. After standardizing all carbon pricing series using Z-scores, their annual equal-weighted mean is then computed. The alternative index, compared with the base CPI index, and the relevant results are presented in Table A-12 of the Appendix.

Circular economy principles play a crucial role in achieving economic development that minimizes resource waste and environmental impact while increasing efficiency across all stages of the product lifecycle, compared to the traditional linear model of 'produce, consume, and dispose.' This approach refers to a system of production and consumption based on recycling, reuse, repair, remanufacturing, product sharing, and shifts in consumption patterns (Mongo et al., 2022; Sangoremi et al., 2025). Accordingly, this study considers key circular economy processes—material footprint, resource productivity, and municipal waste recycling—measured in metric tons, euro/kg, and tons, respectively. The material footprint indicator captures the demand for material extraction (biomass, metal ores, non-metallic minerals, and fossil energy materials) driven by consumption and investment by households, governments, and businesses in the EU. Resource productivity is defined as the ratio of economic output to material consumption, measured as domestic extraction plus imports minus exports. Finally, the municipal waste indicator measures the amount of recycled waste, including material recycling, composting, and anaerobic digestion (Eurostat, 2025).

In the current era of increasing digital transformation, the European Commission Report (2010) suggests that digitalization—through the availability and use of information and communication technologies—can help reduce carbon emissions in EU countries. When integrated into everyday life, digitalization creates new opportunities for preventing and controlling pollution, such as through smart homes and smart cities. Widespread internet access is one of the main indicators used to measure digital transformation (Li, 2024; Eurostat, 2025). For this reason, this study measures digitalization using the share of the population that has used the internet in the last three months.

The last variable is an exogenous regime control, D. It captures the value of zero before 2004 and one from 2004 onward. The binary indicator controls for a broad change in the European institutional and policy environment, associated with the EU movement toward o more integrated European climate-policy regime. To preserve the degree of freedom, D is treated as a single regime indicator, rather than using multiple event specific indicators into a model. It should be noted that the causal direction from the system variable toward D is prohibited through the "Knowledge" specification within TETRAD.

Table 2 reports the descriptive statistics for all the variables used in this study. It is important to note that the variables over the years 2000-2023 are aggregated using cross-country averages.[9] Skewness measures the potential asymmetry of the data, while kurtosis is employed to examine the high and low tails of the variable's distribution. Moreover, a pairwise analysis is conducted to assess the correlation between each pair of variables. For instance, both the scatterplot and the correlation matrices display that carbon emissions are negatively associated with the carbon policy index, renewable energy, resource productivity, and digitalization. However, a positive association is established among CO_2 emissions, material footprint, and energy intensity. The outcomes of the correlation matrix and scatterplot matrix are presented in Figure A-1 and Table A-3 of the Appendix.

5. Results and discussion

5.1. Data preparation and diagnostic tests

Before exploring the causality structure among the variables, several preliminary transformations on the data and diagnostic tests are conducted, including the data distribution visualization, the Zivot-Andrews structural break test, multicollinearity assessment, outlier detection, and the test for the presence of Autoregressive Conditional Heteroskedasticity (ARCH) effects.

[7] Norway and Switzerland are included because they are integrated into the broader EU carbon pricing framework. Norway participates in EU-ETS and Switzerland operates a link emissions trading system (ETS).

[8] Please refer to the PCA construction of the Carbon policy index in Table A-10 of the Appendix.

[9] The T = 24 time series observations for each variable are obtained using cross-country averages on the original, untransformed variables in levels, via the "collapse" command in Stata.

Table 2
Descriptive statistics.

Variable	OBS	Mean	Std. dev.	Min	Max	Skewness	Kurtosis
CO_2	24	1.18×10^8	1.28×10^7	9.09×10^7	1.34×10^8	−0.44	2.21
CPI	24	0.069	0.75	−0.62	2.36	1.90	6.11
RE	24	92.33	26.16	56.70	141.21	0.17	1.72
EI	24	1.81	0.33	1.28	2.40	0.31	2.03
MF	24	26.85	2.16	23.87	31.78	0.98	2.98
RP	24	1.81	0.33	1.51	2.30	0.38	2.009
MW	24	3.4×10^6	732031.1	2.3×10^6	4.9×10^6	0.28	2.19
IPR	24	66.78	20.38	21.44	91.27	−0.80	2.58

The transformation applied to all variables before the DAG causality analysis is two-fold. First, the variables are transformed into logarithms and then converted into first differences, to ensure stationarity and to remove trends. Second, the differenced series are standardized using z-scores.[10]

To examine the distributional characteristics of the transformed variables, kernel density plots are used. As shown in Fig. 1, most variables exhibit asymmetric distributions, although moderate skewness appears in some cases, particularly for the variable's digitalization and resource productivity.

The Zivot-Andrews test (see Table 3) identifies different trend breaks in most of the transformed variables, suggesting that policy or economic changes across the countries may have altered their long-term behaviour. The breaks appear in the transformed variables related to emissions, energy transition, circular economy practices. Also digitalization may reflect adjustments following a combination of economic, institutional, and policy changes. The post-2004 indicator included in the FASK analysis operates as a broad institutional-regime control, rather than as a variable specific break analysis. For instance, the breaks in resource productivity and digitalization in 2020 coincide with the COVID-19 period.

To investigate the potential multicollinearity among the explanatory transformed variables, the variance inflation factor (VIF) and the tolerance (1/VIF) are employed. Based on Table 4, the maximum VIF score is 1.63, and the minimum (1/VIF) score is 0.61, both far from the conventional thresholds adopted to indicate the presence of multicollinearity. These outcomes confirm that the explanatory transformed variables are not highly correlated with each other, and that multicollinearity is not an issue.

Standardized residuals from the OLS regression of transformed CO_2 on transformed CPI, RE, EI, MF, RP, MW IPR, and a constant term are used in this work to assess any outliers, namely the residuals-fitted values plot in Fig. 2. It is evident that around 68% of observations fall within [−1, 1] standard deviations, 95% within [−2, 2] standard deviations, and 99.7% within [−3, 3] standard deviations. The residuals do not surpass the [−2, 2] standard deviations threshold, which is typically regarded as a sign of possible outliers, and are spread around zero. A few observations, which come between 2018 and 2020, do depart from the center, but they are still within reasonable bounds. As a result, the findings imply that there isn't a serious outlier issue with the dataset.

The carbon equation regressing transformed CO_2 on transformed CPI, RE, EI, MF, RP, MW IPR, and a constant term is tested for Autoregressive Conditional Heteroskedasticity (ARCH) using the ARCH-LM test. Since the null hypothesis of no ARCH effect up to lag 1 is not rejected at standard significance levels, the results in Table 5 support the idea that the residuals are homoscedastic (constant conditional variance). The lack of ARCH effects could be explained by the data's annual periodicity, which often lessens volatility clustering.

In order to identify the presence of potential long-run equilibrium relationships among the original variables, the Johansen cointegration test is conducted.[11] First, the Augmented Dickey-Fuller (ADF) test is applied to examine the stationarity of the variables. As results indicate (see Table 6), all variables are stationary at first differences, which satisfies the prerequisite for employing the Johansen test. Second, the optimal lag length of one is determined for the underlying unrestricted VAR. Third, the trace statistics in Table 7 reject the null hypothesis of no cointegration (rank = 0,1), but fail to reject the null hypothesis of rank = 2. Therefore, the results suggest a possible long-run co-movement among the variables under analysis. Fourth, the “alpha” coefficients, i.e. the speeds of adjustment toward the long-run equilibrium, are significant and respond reasonably to disequilibrium in the system (see Table 8). In particular, CO_2 and several explanatory variables, including renewable energy share, energy intensity, material footprint, and internet penetration rate, adjust to restore long-run equilibrium. Lastly, the “beta” coefficients reported in Table 9 indicate the long-run equilibrium relation among the variables. These coefficients are interpreted as supplementary evidence, suggesting possible long-run co-movement between renewable energy, energy intensity, municipal waste, and internet penetration rate in the system.

5.2. Causality

Fig. 3-a, Fig. 3-b and Table 10 present the DAG results for the short-run and long-run causal structures produced by the FASK algorithm. Differenced and standardized (i.e., transformed) variables, their lagged values, and a dummy variable are employed to estimate the short-run causal structure.[12] In the long-run analysis, the Equilibrium Correction Term (ECT), derived from the Johansen cointegration procedure, is additionally incorporated in the causal structure. The inclusion of the ECT enables the causal structure to reflect not only contemporaneous short-run causal directions but also long-run adjustment dynamics that arise from deviations from the system's equilibrium.

The short-run findings (Fig. 3-a and Table 10) show that several explanatory factors, including resource productivity (RP), material footprint (MF), and internet penetration rate (IPR), are directly linked to CO_2 emissions. This indicates that variations in digitalization, material consumption, and resource efficiency can immediately affect CO_2 emissions. The direct role of digitalization in influencing emissions in the EU is supported by Maftei et al. (2025), whose results show that digital infrastructure affects emissions directly in the short term via technological change. Empirical evidence from Wang et al. (2024) and Prapaspongsa et al. (2024) further confirms that material flows have a

[10] The rationale for this transformation is that the FASK algorithm used in the DAG causality analysis with the software TETRAD relies on non-Gaussian distributional characteristics of the data and requires stationarity as well as comparable-scale variables in order to correctly identify causal directions. Specifically, FASK exploits distributional asymmetries to orient edges, handles cycles, latent confounders, and feedback structures, and it is reliable also in presence of weakly-linear or partially-monotonic relationships.

[11] The integration/cointegration analysis is applied to the original variables, expressed in logarithms. Given the limited number of observations, the test is used as supplementary evidence of possible long-run co-movements.

[12] lX indicates the one-period lag of variable X, with X = CO_2, CPI, RE, EI, MF, RP, MW, IPR, ECT. ECT indicates the Error Correction Term.

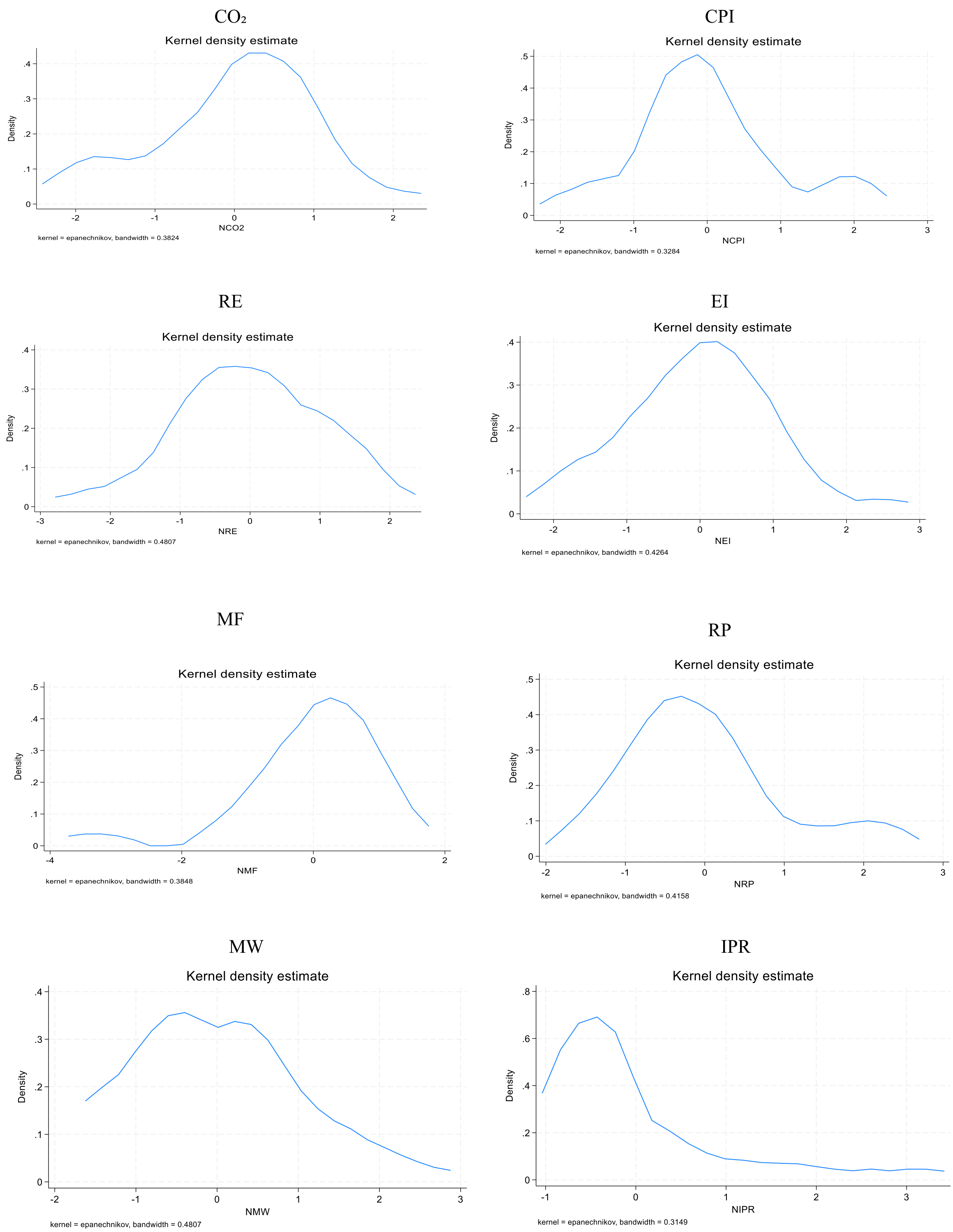


Fig. 1. Variable distributions (transformed data)
*Note: The horizontal axis indicates the standardized transformed values of each variable and the vertical axis represents the estimated density.

direct impact on emissions. Mushafiq and Prusak (2023) and Sen et al. (2021) find that resource productivity, i.e. the economic output generated per unit of resources, can substantially shape environmental degradation in EU countries, which is highly consistent with our results.

A closer examination of the short-run relationships reveals that changes in emissions are not driven by a single isolated determinant. Instead, the evidence points to joint effects among several variables—material footprint, municipal waste, renewable energy, and internet penetration rate—operating through resource productivity as a key mediating channel. These interdependencies suggest that improvements in one dimension, such as digitalization, can enhance resource productivity, and thereby transmit effects to CO_2 emissions. This mechanism is conceptually in line with the EU's integrated decarbonization strategy. Studies including Bibri et al. (2024), Wang et al. (2024), Tang et al. (2024), and Sen et al. (2021) similarly document joint effects in decarbonization processes.

Table 3
Structural breaks.

Variable	Zivot Andrews unit root test with structural breaks		
	Break Type	Year	Plausible Reason
CO_2	Trend	2010	ETS Phase III
CPI	-	-	-
RE	Trend	2006	Renewables Acceleration
EI	Trend	2018	Clean Energy Package
MF	Trend	2010	Industrial Transition
RP	Trend	2020	Green Deal/COVID-19
MW	Trend	2004	CE Reforms
IPR	Trend	2020	Green Innovation Surge

Table 4
Multicollinearity.

Variable	Multicollinearity test	
	VIF	1/VIF
Mean	1.48	0.67
CPI	1.31	0.76
RE	1.43	0.69
EI	1.54	0.65
MF	1.63	0.61
RP	1.49	0.67
MW	1.48	0.67
IPR	1.51	0.66

Note: For the *j*-th explanatory variable ($j =$ CPI, RE, EI, MF RP, MW, IPR) in the OLS regression model where the dependent variable is CO_2, $VIF_j = 1/(1\text{-}R_j^2)$, where R_j^2 is the R^2 of the regression of the *j*-th explanatory variable on all the other explanatory variables. Tolerance $= 1/VIF_j = 1\text{-}R_j^2$. "Mean" indicates the simple average calculated on the single VIFs (single Tolerances). If $VIF_j < 5$, then multicollinearity is low.

Table 5
ARCH-LM test.

Lag(s)	Chi2	df	p-value
1	1.10	1	0.29

To capture potential structural or regime changes after 2004 that may have affected the dynamics of emissions in the EU during the period examined, a step (regime-shift) dummy variable is additionally incorporated into the causality framework. The results indicate that this dummy variable affects emissions indirectly via resource productivity, implying that structural shifts can alter the efficiency of resource use and, in turn, influence emissions. However, since no direct path from the dummy variable to CO_2 emissions is identified, the model does not detect any immediate, direct regime-shift or policy shock in the system.

Table 6
ADF tests.

Variables	ADF – I(1)
CO_2	−4.48***
CPI	−2.51*
RE	−3.59***
EI	−3.48***
MF	−3.22***
RP	−2.86**
MW	−4.60***
IPR	−4.69***

Note: ***, *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The ADF tests are applied to each variable in first-differences, hence rejecting the null hypothesis of a unit root means that the variable is I(1) in log-levels.

Table 7
Trace and rank tests.

Rank	Params	LL	Eigenvalue	Trace statistic	Critical values at 5%
0	8	317.39	0	192.16	156.00
1	23	349.64	0.93	127.66	124.24
2	36	369.15	0.81	88.65*	94.15

In the long run (Fig. 3-b and Table 10), the one-period lagged ECT-based DAG provides additional exploratory information.[13] This extension of the DAG reflects the idea that when the system deviates from its long-run equilibrium, some variables such as energy intensity, internet penetration rate, and municipal waste gradually readjust towards the

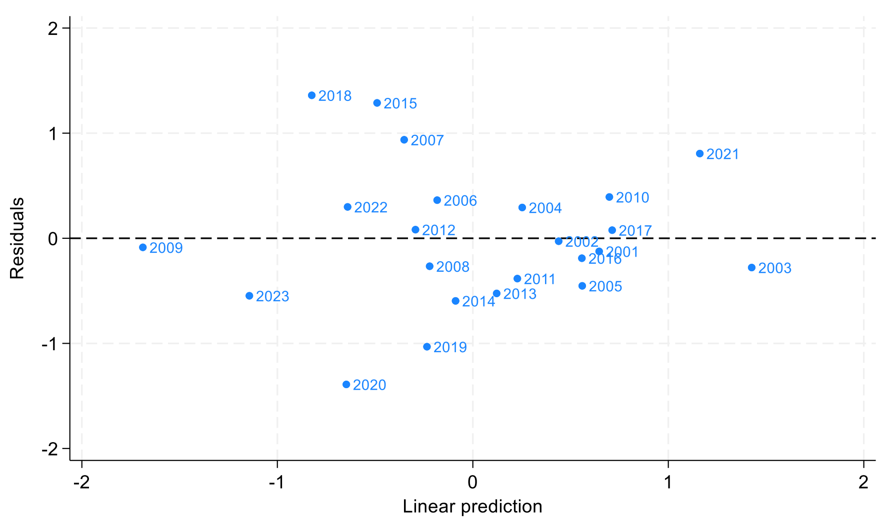


Fig. 2. Residual-fitted value plot.

[13] The long-run DAG/FASK framework includes the one-period lagged error correction term in line with the conventional error correction framework. The results are interpreted as exploratory evidence of whether/how previous-period disequilibrium is connected to the system's adjustment.

Table 8
Error correction - loadings.

Alpha	Coef (l.ce1)	SD	Z	p-value
CO_2	−0.32***	0.09	−3.60	0.00
CPI	−0.23	1.04	−0.23	0.82
RE	0.26**	0.11	2.30	0.02
EI	−0.09*	0.04	−1.88	0.06
MF	−0.24**	0.11	−2.17	0.03
RP	0.07	0.05	1.20	0.23
MW	0.10	0.07	1.36	0.17
IPR	−0.74***	0.13	−5.42	0.00

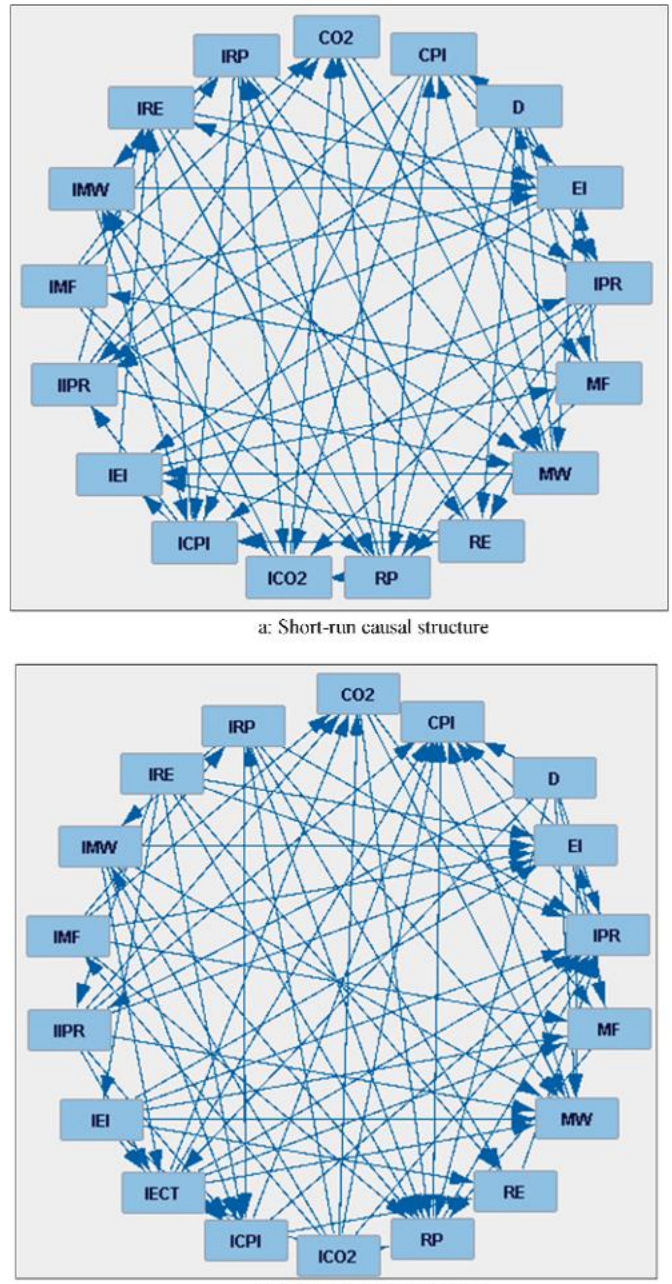
Note: ***, *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Z indicates asymptotic *t*-test.

Table 9
Long-run cointegrating vector.

Beta	Coef (l.ce1)	SD	Z	p-value
CO_2	1			
CPI	0.05***	0.13	3.80	0.00
RE	0.28***	0.10	2.66	0.00
EI	−1.02***	0.33	−3.10	0.00
MF	0.05	0.13	0.40	0.68
RP	0.22	0.23	0.93	0.35
MW	−1.41***	0.22	−6.33	0.00
IPR	0.13***	0.02	4.58	0.00

Note: ***, *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Z indicates asymptotic *t*-test.

system equilibrium. This finding is reflected in the lECT node, which transmits to lEI, lIPR, lCO_2, and MW, suggesting potential adjustment channels through which the system balance restores from disequilibrium. This outcome is consistent with the beta coefficients reported in Table 9, where several variables, such as energy intensity, renewable energy, carbon policy index, municipal waste, and internet penetration rate, are found to have statistically significant relationships with CO_2 emissions. In other words, the long-run analysis suggests that previous-period disequilibrium in the system may be adjusted through improvement in energy transition, digitalization, and waste management recycling technologies. The results indicate, first, a direct adjustment pathway, lECT → lCO_2 → CO_2, meaning that CO_2 seems to be associated with deviations from the previous-period equilibrium. Second, the system also restores equilibrium through an indirect pathway, lECT → lEI, in which changes in energy intensity relate to digitalization, material use, municipal waste, and renewable energy, ultimately transmitting to CO_2 through digitalization and renewable energy. This mechanism also suggests that, when the system becomes unbalanced, structural adjustments in energy efficiency may occur, and subsequently be transmitted through circular economy practices and digitalization to CO_2 emissions. A similar mechanism is also described in Zhou (2023) and Shobande et al. (2024), who show that long-term decarbonization pathways depend heavily on energy efficiency improvements. Third, the system shows a potential adjustment pathway through the digitalization channel, lECT → lIPR. Structural changes in the digital infrastructure and technological devices influence CO_2 emissions. Finally, adjustment also occurs through municipal waste channels, lECT → lMW, meaning that structural changes in the municipal waste recycling process may influence resource efficiency and subsequently CO_2 emissions. Wang et al. (2024) and Prapaspongsa et al. (2024) confirm that circular economy practices are a long-run channel of CO_2 mitigation in the EU. In terms of the causal network, the structure suggests relatively stable interconnected relationships among the variables in the long run, similar to the short-run structure. Additionally, resource productivity remains a key mediating factor in both horizons, which provides supplementary evidence on the robustness of the causal pathways over time.



a: Short-run causal structure

b: Long-run causal structure

Fig. 3. Causal structures.

Table 10
Summary of short-run and long-run causal transmission structures.

Time Horizon	Transmitters to CO_2	Mediator	Transmitters to Mediator	Mechanism
Short-run	RP, lCO_2, lIPR, lMF	RP	D, IPR, MF, lCO_2, lMF, lMW, lRE, lRP	
Long-run	RP, lCO_2, lIPR, lMF,	RP	D, lCO_2, lMF, lMW, lRE, lRP, MF	lECT transmitted to lEI, lIPR, lMW, lCO_2

Note: lX indicates the one-period lag of variable X, with X = CO_2, CPI, RE, EI, MF, RP, MW, IPR, ECT. ECT indicates the Error Correction Term, while D is the step dummy variable, equal to 1 from 2004 to 2023 and equal to 0 otherwise.

5.3. Connectedness

In this section, both static and dynamic copula models are used to describe the dependence structure and the level of interconnectedness among the variables in the causality network. Specifically, the study employs time-varying copula models based on the ARMA process, as proposed by Patton (2006). Copulas are fitted to the residuals obtained after modeling each log-transformed variable with an ARMA(p,q) process, where the orders p and q are determined using standard information criteria. The estimation results of the copula models—including the selected copula family, the log-likelihood values, Kendall's Tau coefficients, and the corresponding evolution plots—are reported in Table 11. For each copula, the optimal specification of the dependence structure, including the lag order, is chosen according to the minimum AIC value.

For the pair CO_2 and digitalization (CO_2, IPR), the t-student is the best model among all the selected static copulas to fit the joint distribution, with a Kendall's tau of 0.20. This symmetric tail dependence suggests that increases in internet usage during low and high extreme periods tend to be associated with higher emissions. The time-varying copulas generally outperform to that of static models, as the selected information criteria (e.g. AIC) suggests. Looking at dynamic dependence, the time-varying Clayton copula represents the best fit for the dependence structure of the (CO_2, IPR) pair, with a degree of volatility dependence ranging between [0.19 and 0.35]. Since the Clayton model captures lower-tail dependence, the two variables tend to move together, not only at average values, but also when both variables exhibit relatively low values. In other words, the stronger association between emissions and internet usage is registered in correspondence with a lower or early-development stage of digitalization. In terms of interconnectedness, the degree of dependence is weak before 2006, but it rises following the Digital Expansion—the early spread of online platforms and digital networks[14]—and the launch of the "Digital Agenda for Europe" program in 2010, which aimed to improve access to digital goods and services and to harness the growth potential of Europe's digital economy (EU4Digital,[15] 2025). From 2018 to 2020, this relationship weakened again due to the rise of green digitalization initiatives.[16] Yet, the COVID-19 outbreak in 2020, which boosted remote and digital work, together with the "EU Digital Decade Strategy" program, brought the dependence back to a moderate level. These findings are consistent with Park et al. (2018), who report significant and positive effects of increasing internet use on emissions.

A moderate, positive dependence (0.32) is identified for the (CO_2, MF) pair when applying the Clayton copula. This finding suggests that upstream circular economy activities, especially material extraction, are associated with carbon emissions in the EU, a relationship also highlighted in the literature, for example by Ghisellini et al. (2016). Regarding the dynamic dependence structure, the time-varying rotated-Gumbel copula indicates that the two variables tend to move together in periods when both reach high values, although the strength of this linkage fluctuates over time. Before 2005, this evolution follows a bell-shaped pattern, then stabilizes during the financial debt crisis, and shows a slight increase in the post-COVID phase. In the period of strong dependence between 2000 and 2005, Kendall's tau rose sharply from 0.30 to 0.89, potentially reflecting episodes of intensified economic activity and material use that may have heightened environmental pressure. From 2007 to 2020, the financial debt crisis, coupled with EU circular economy policies, placed growing emphasis on sustainable material management, which may have contributed to a 5.5% reduction in the per capita material footprint trend; correspondingly, Kendall's tau remains below 0.4. Moreover, a central objective of the 8th Environment Action Programme, the "2020 Circular Economy Action Plan," is to keep the material footprint within planetary boundaries by doubling circular material use. In line with this, recent statistics indicate a notable 6.2% decline in material footprint between 2022 and 2023, mainly driven by reduced metal and fossil resource consumption across the EU, which could lower the dependence measure to below 0.3 (EEA,[17] 2024).

Among the CO_2-related pairs, the resource productivity reveals the strongest association in absolute Kendall's tau terms, highlighting the role of circular economy measures—especially sustainable resource management—in shaping environmental quality in the EU. The t-student copula model estimated for the (CO_2, RP) pair indicates a negative and moderate dependence. This outcome underlines the inverse relationship between resource efficiency and carbon emissions across the EU, consistent with the findings of Mushafiq and Prusak (2023) and Sen et al. (2021). Regarding the dynamic dependence structure, a time-varying t-student copula with symmetric tail dependence best captures the joint distribution of the pair. The strength of dependence fluctuates between -0.37 and -0.05, remaining persistently negative over the entire period. The dependence level in 2002 (-0.37) implies that gains in resource efficiency were strongly associated with reductions in CO_2 emissions. From 2003 to 2010, the relationship stayed negative but weakened significantly over time. This trend stabilized between 2010 and 2017, largely due to the rollout of circular economy policies, particularly the EU's resource efficiency strategy. Following the G20 "Resource Efficiency Dialogue" [18] in July 2017, new avenues emerged to advance the global shift toward resource efficiency, which loosened the linkage between the two variables and reduced Kendall's tau to zero.

The static dependence structure linking resource productivity, as a mediating variable, with internet penetration, material footprint, municipal waste, and renewable energy is captured using symmetric Student-t and SJC copulas. Among these, material footprint shows the strongest negative correlation with resource productivity, in line with the circular economy literature. This pattern implies that greater efficiency in the use of resources lowers the need for material extraction, thereby helping to preserve environmental quality (Mushafiq and Prusak, 2023). For the digitalization–resource productivity pair, the analysis reveals a positive but weak dependence. This finding indicates a modest yet positive co-movement between digital and technological progress and sustainable resource use, consistent with Bibri et al. (2024). Municipal waste and renewable energy both exhibit a positive, moderate link with resource productivity, suggesting that gains in resource efficiency are associated with more sustainable recycling activities and a cleaner energy mix (see Perdiguero and Sanz, 2025). Regarding dynamic dependence, the sign of the relationships remains unchanged, although their intensity varies across pairs. The strongest and most volatile connections are found for the (RP, MW) and (RP, RE) pairs when modeled with a time-varying SJC copula, especially in the upper tail. When resource productivity is high, it tends to be accompanied by higher levels of municipal waste and renewable energy. The upper-tail plot for the (RP, MW) pair displays a bell-shaped pattern: initially, resource productivity and recycling activities move closely together, but they gradually decouple following the 2017 resource efficiency dialogue. A similar evolution appears in the (RP, RE) pair, where a strong pre-2013 association progressively weakens thereafter. This outcome supports Sen et al. (2021), who examine the interplay between energy transition and resource productivity. In parallel, enhanced resource management shows a dynamic interaction with substantial technological advances, as evidenced by a time-varying

[14] EU information society policy milestone from 2002 to 2020. Details at: https://ec.europa.eu/eurostat/web/main/home.

[15] More information on EU4Digital can be found at: https://eufordigital.eu/.

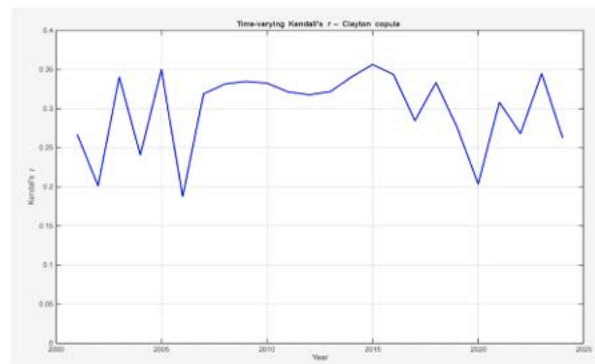
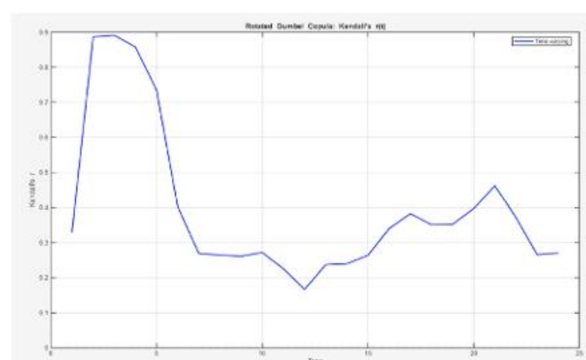
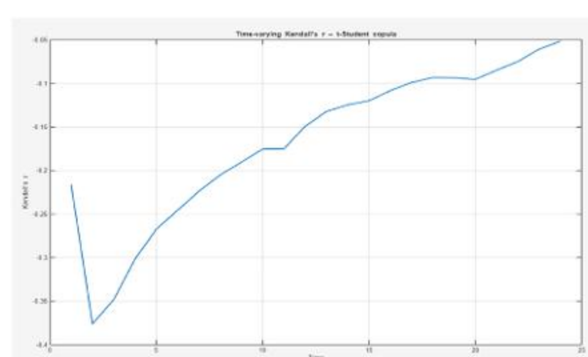
[16] 4.3 Greening ICT. Details at: https://ec.europa.eu/assets/rtd/srip/chapter4.3.html.

[17] European Environment Agency. Details at: https://www.eea.europa.eu/en.

[18] https://commission.europa.eu/system/files/2020-06/european-semester_thematic-factsheet_resource-efficiency_en_0.pdf.

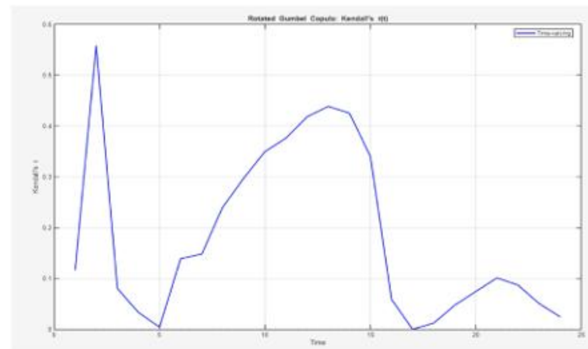
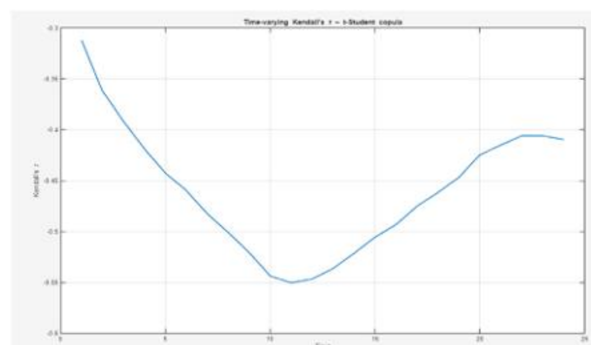
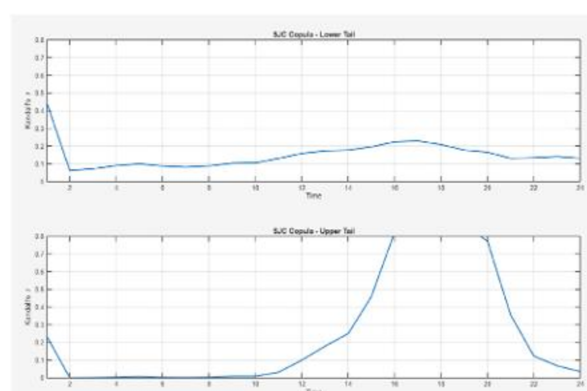
rotated Gumbel copula. The dynamic plots indicate that the expansion of digital infrastructure in the EU after 2006 reinforced the link between internet use and resource productivity, although this relationship weakened and declined after the launch of the Green Digital and Digital Agenda for Europe (2010) initiatives. The negative dependence between circular economy practices, represented by (RP, MF), stabilizes between approximately −0.55 and −0.31. The findings of Ghisellini et al. (2016) and Mushafiq and Prusak (2023) corroborate the mechanism through which higher resource productivity alleviates material extraction pressures, thereby supporting these results. Nonetheless, the dynamic evolution of dependence shows that this negative connection becomes more pronounced following the implementation of circular economy

Table 11
Estimated Copula models.

Pairs	Opt-Lag (AIC)	STATIC	DYNAMIC
		BiCop	BiCop
(CO_2, IPR)	(1,1)	Family[a] = 8 LL = −0.60 Tau = 0.20	Family = 13 LL = −3.01 Tau: [0.19, 0.35]
			
(CO_2, MF)	(1,1)	Family = 2 LL = −3.37 Tau = 0.32	Family = 11 LL = −6.14 Tau = [0.16, 0.89]
			
(CO_2, RP)	(1,1)	Family = 8 LL = −2.67 Tau = −0.33	Family = 15 LL = −2.89 Tau = [-0.37,-0.05]
			
(RP, IPR)	(1,1)	Family = 9 LL = −0.76 Tau = 0.02	Family = 11 LL = −2.17 Tau = [0.001, 0.55]

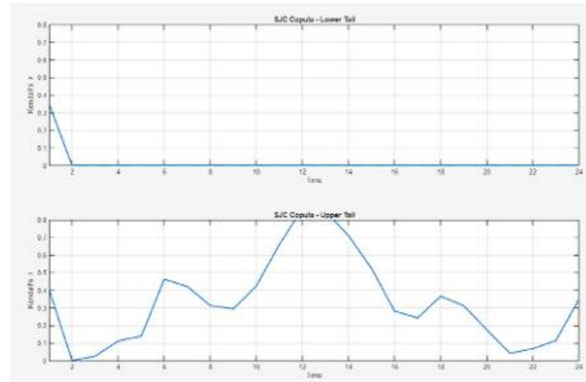
(*continued on next page*)

Table 11 (*continued*)

Pairs	Opt-Lag (AIC)	STATIC	DYNAMIC
		BiCop	BiCop
			
(RP, MF)	(1,1)	Family = 8 LL = −2.44 Tau = −0.47	Family = 15 LL = −3.60 Tau = [-0.55, −0.31]
			
(RP, MW)	(1,1)	Family = 8 LL = −3.28 Tau = 0.34	Family = 12 LL = −7.71 Tau = [0.001, 0.95]
			
(RP, RE)	(1,1)	Family = 9 LL = −3.42 Tau = 0.23	Family = 12 LL = −5.90 Tau = [0.001, 0.86]

(*continued on next page*)

Table 11 (*continued*)

Pairs	Opt-Lag (AIC)	STATIC	DYNAMIC
		BiCop	BiCop
			

[a] List of the copula families: 1: Normal (Gaussian), 2: Clayton, 3: Rotated-Clayton, 4: Plackett, 5: Frank, 6: Gumbel, 7: Rotated-Gumbel, 8: t-Student, 9: Symmetrized Joe-Clayton (SJC), 10: Time-varying Normal, 11: Time-varying Rotated-Gumbel, 12: Time-varying SJC, 13: Time-varying Clayton, 14: Time-varying Gumbel, 15: Time-varying t-Student.

measures and the “Resource Efficiency Dialogue”.

5.4. Forecasting CO_2 trends

The study employs Support Vector Regression (SVR) models, which are well suited to projecting future CO_2 paths affected by multiple drivers. To improve the accuracy of CO_2 trend forecasts, the analysis integrates the European Commission’s 2030 climate targets: 1) municipal recycling is expected to rise by 47.5%, 2) resource productivity is set to increase by 30%, 3) the Emission Trading System aims to reduce emissions by 62%, 4) renewable energy is targeted to reach a 42.5% share of the energy mix, and 5) digitalization is anticipated to contribute a 20% improvement in decarbonization. For the single-stage forecasting framework, two variants are tested: a basic SVR and a Tuned SVR (TSVR). For the two-stage framework, an ARIMA model is first applied, followed by the TSVR used in the single-stage setup. The basic SVR attempts to fit a function that balances accuracy with parsimony by constraining errors within a predefined margin and penalizing larger deviations. This baseline model is estimated using three kernel functions—linear, polynomial, and radial. Based on average forecast errors across all specifications, the radial kernel provides the best fit, yielding the smallest prediction errors (see Table A-4 and Figure A-2 in the Appendix). The TSVR model is then obtained by optimizing key hyperparameters through cross-validation to enhance model stability and predictive accuracy.[19] The hyperparameters Cost, Gamma, and Degree are user-specified but data-driven in that they are selected through five-fold cross-validation to regulate model complexity and improve out-of-sample performance. Following the tuning protocol, cross-validated forecast accuracy is used to determine the optimal parameter values. The lowest prediction errors occur when epsilon lies between 0.2 and 0.4; for tractability, the degree is fixed at 2, and the results indicate that forecast performance is relatively insensitive to the Cost parameter (see Figure A-3 in the Appendix). For the two-stage model, the ARIMA process is first used to capture the linear component of emissions, and the TSVR is then applied to the residuals to model the remaining nonlinear structure.

Tables 12 and 13 compare the performance of the one-stage and two-stage forecasting models and their projected emission trajectories. The forecasting indicators, including MAE and MAPE, suggest the superior performance of TSVR among the estimated models. However, its RMSE is slightly lower than that of the basic SVR. The hybrid ARIMA-TSVR model exhibits higher average errors than the simpler SVR models. This suggests that simpler SVR specifications provide acceptable indicative forecasting performance, while capturing the nonlinear forecasting patterns. Therefore, TSVR is selected as the preferred model for the main policy interpretations.

Table 12
Forecasting performances of SVR, TSVR and ARIMA-TSVR models.

Method	SVR	TSVR	ARIMA-TSVR
RMSE	2702140	2692648	3148361
MAE	1893735	1467146	2054606
MAPE	1.68	1.32	1.89

The values reported in Table 13 and Fig. 4-a to 4-c represent the indicative CO_2 emission forecasts, which decline year by year. All three models suggest a downward trajectory in carbon emissions across countries from 2024 to 2030, indicating that existing structural changes, energy policies, and circular economy initiatives may contribute to climate mitigation goals. Although the ARIMA-TSVR hybrid model projects slightly lower emission levels, it is associated with higher average forecast errors, therefore is not selected for the main policy interpretations. Based on its relatively superior performance according to the RMSE, MAE, and MAPE criteria, the TSVR model is preferred for the main policy discussion. Within the TSVR framework, emissions decline from approximately 96 Mt in 2024 to around 79.8 Mt by 2030, suggesting a substantial reduction. Nonetheless, the gap between the forecasted value and the target level in 2030—approximately 16.8 Mt—is still considerable, suggesting that additional or revised policies may be needed to fully achieve the decarbonization objectives. Importantly, although the estimated policy gap depends on model choice and ranges from 16.47 to 17.07 Mt across the three models, the conclusion that projected emissions remain above the 2030 target is consistent across all specifications. These findings align with the IPCC's Sixth Assessment Report (2022), which concludes that current policy pathways in many regions may be inadequate to meet long-term climate goals without further intervention. Likewise, the EEA (2024) points out that, although EU carbon emissions have declined in recent decades, further policy action may be needed to achieve the 2030 targets.

To account for forecasting uncertainty, indicative 95% residual-bootstrap prediction intervals are estimated for the selected TSVR

[19] The hyperparameter Cost controls the penalty for prediction error; the hyperparameter Gamma determines the memory usage in nonlinear kernels; the hyperparameter Degree specifies the curve complexity.

Table 13
Levels (tons) of CO_2 emissions forecasted by SVR, TSVR, and ARIMA-SVR models.

Year	SVR	TSVR	ARIMA-TSVR
2024	93,643,497.00	96,064,847.70	89,363,200.00
2025	91,371,831.00	93,083,856.20	87,715,694.00
2026	88,817,473.00	89,639,775.10	86,066,994.00
2027	86,514,650.00	86,649,946.80	84,418,294.00
2028	84,348,305.00	84,180,937.60	82,769,593.00
2029	82,208,408.00	81,964,738.70	81,120,893.00
2030	80,070,357.00	79,818,487.40	79,472,193.00
Policy Gap (target vs forecast)	17,070,357.00	16,818,487.40	16,472,193.00

model using 2000 replications[20]. Fig. 4-d shows that emissions are projected to decline from 96.06 Mt in 2024 to 79.82 Mt in 2030. Also, the estimated policy gap is 16.81 Mt with an indicative 95% interval ranging from 11.88 to 26.72 Mt. However, the relevant prediction interval ranges from 74.88 to 89.72 Mt, suggesting that the projected emissions remain above the EU target (63 Mt) after accounting for estimated forecasting uncertainty.

5.5. Sensitivity analysis and robustness checks

To assess how CO_2 emissions at the 2030 baseline respond to marginal changes in the explanatory variables, a local sensitivity analysis is conducted. As shown in Fig. 5, a 1% increase in each variable leads to changes in emissions (tons), with both positive and negative contributions to CO_2 levels. Circular economy measures, particularly resource productivity, exhibit a positive marginal effect, corresponding to an approximate increase of 634 (tons) increase in CO_2 emissions for a 1% increase in RP. This result appears to contrasts with the negative dependence between RP and CO_2 identified in the DAG and copula analyses. These findings capture different effects: The DAG and copula analysis describe the system-level role and connectedness of RP, while the sensitivity analysis measures its isolated marginal effect (other factors are kept constant). Conceptually, the total effect of RP on CO_2 emissions is equal to the sum of the efficiency effect and scale/rebound effect. Accordingly, RP reduces CO_2 emissions when the negative efficiency effect is larger than the positive scale/rebound effect.[21] Therefore, the positive marginal result suggests that RP individually may be partly offset by increased consumption/production. This phenomenon may reflect plausible rebound or scale effects. Likewise, higher municipal waste generation is associated with larger emissions at the margin, while the material footprint variable has a relatively small, although still positive, marginal effect. Expanded internet use also slightly raises emissions by around 7 (tons). In contrast, indicators related to the energy transition and carbon pricing instruments are negatively associated with CO_2 emissions, underscoring their central role in supporting decarbonization. Furthermore, Table 14 indicates the optimized scenario identified within the defined limits, with predicted CO_2 emissions of 79.81 Mt. This scenario remains above the EU's climate target, with the expected CO_2 emissions of approximately 63 Mt. The findings indicate that circular economy practices, in particular municipal waste requires a substantial reduction of 28.86% relative to the baseline. The small increase in resource productivity in the optimized scenario, despite its positive marginal effects in Fig. 5, may reflects scale and rebound effects, whereby improvements in resource efficiency can stimulate additional economic activity, waste generation, and emissions. This aligns with the EEA (2025) report, which argues that efficiency measures alone are inadequate and may ultimately increase resource use over the long term. For municipal waste, we find both a positive marginal effect and a substantial required negative adjustment. Although waste management, particularly recycling, is widely regarded as environmentally beneficial, EEA (2025) and Bianchi and Cordella (2023) highlight the energy-intensive nature of recycling and its constrained long-term effectiveness across European countries. By contrast, the needed adjustments in material footprint, energy intensity, emissions trading systems, and carbon taxes are already consistent with the decarbonization trajectory. Taken together, the marginal effects and policy adjustments underscore the pivotal influence of circular economy strategies, especially resource productivity, in achieving decarbonization objectives.

A robustness assessment of FASK's causal structure is carried out using bootstrapping.[22] As reported in Table 15, the causal links identified by the FASK algorithm for European countries are robust in both the short-run and long-run specifications. The edge stability analysis reveals a coherent and stable causal pattern. Within the DAG model, digitalization emerges as the most stable variable, indicating a strong and enduring influence. Resource productivity and material footprint display moderate to high stability, underscoring their central importance as channels in the system. By contrast, the edge stability of energy intensity, renewable energy, and the carbon policy index is comparatively weaker than that of the other variables. Overall, these findings confirm that the causal structure remains stable across the short-run and long-run specifications.

Fig. 6 presents the results of the robustness analysis for the system's degree of connectedness.[23] Both the direction and magnitude of the relationships remain almost unchanged, confirming the stability of the dependence structure. The static C-vine outcomes indicate that CO_2 acts as the central dependence node, with all other variables linked directly to it. In Fig. 6, CO_2 shows a strong dependence on circular economy practices, particularly on the material footprint, underscoring its crucial impact on CO_2 emissions. In contrast, digitalization has no direct connection with emissions in the system, implying that its influence may be indirect or delayed. The dependencies on material footprint and energy intensity are also positive, whereas the remaining dependencies are negative.

The robustness of the results to shocks is examined using a lagged sensitivity analysis. This involves introducing shocks to the explanatory variables in 2029 and then assessing their impact on emissions in 2030. In Fig. 7, the marginal effects become more pronounced in the lagged specification, underscoring the system's propensity to accumulate

[20] It's worth noting that the prediction intervals show the uncertainty around the forecast and do not remove the limitation of the small sample. For this aim, the forecasts should therefore be interpreted as indicative rather than precise estimates

[21] It is possible to decompose the total impact of RP on CO2 into direct and indirect effects, where the indirect effects come from K variables X_i ($i = 1, \ldots, K$) that affect CO2 and are affected by RP. Formally:

$$CO_2 = f(RP; X_1(RP); X_2(RP); \ldots; X_i(RP); \ldots; X_K(RP))$$

The total impact of RP on CO2 is then:

$$\frac{dCO_2}{dRP} = \frac{\partial CO_2}{\partial RP} + \left(\frac{\partial CO_2}{\partial X_1} \times \frac{\partial X_1}{\partial RP}\right) + \ldots + \left(\frac{\partial CO_2}{\partial X_i} \times \frac{\partial X_i}{\partial RP}\right) + \ldots + \left(\frac{\partial CO_2}{\partial X_K} \times \frac{\partial X_K}{\partial RP}\right) =$$

$$= \frac{\partial CO_2}{\partial RP} + \sum_{i=1}^{K} \left(\frac{\partial CO_2}{\partial X_i} \times \frac{\partial X_i}{\partial RP}\right)$$

where the first term indicates the direct effect, whereas the second term is the sum of the indirect effects.

[22] The method used by TETRAD is a nonparametric bootstrap with replacement, which takes in to account the time-series nature of the variables. Bootstrapped values of variable X are obtained by drawing of size T from the estimated sample distribution of X. The number of draws is set to 10,000.

[23] In Fig. 6, the degree of connectedness between CO_2 and each X (X = CPI, RE, RP, IPR, EI, MW, MF) is measured by taking into consideration the presence of all the other Xs. Each edge label reports the selected copula family and the corresponding Kendall's tau coefficient. Negative values indicate inverse dependence between the connected variables. Positive values indicate co-movement. Node 1 (CO_2) acts as the central dependence node, with all remaining variables linked directly to it.

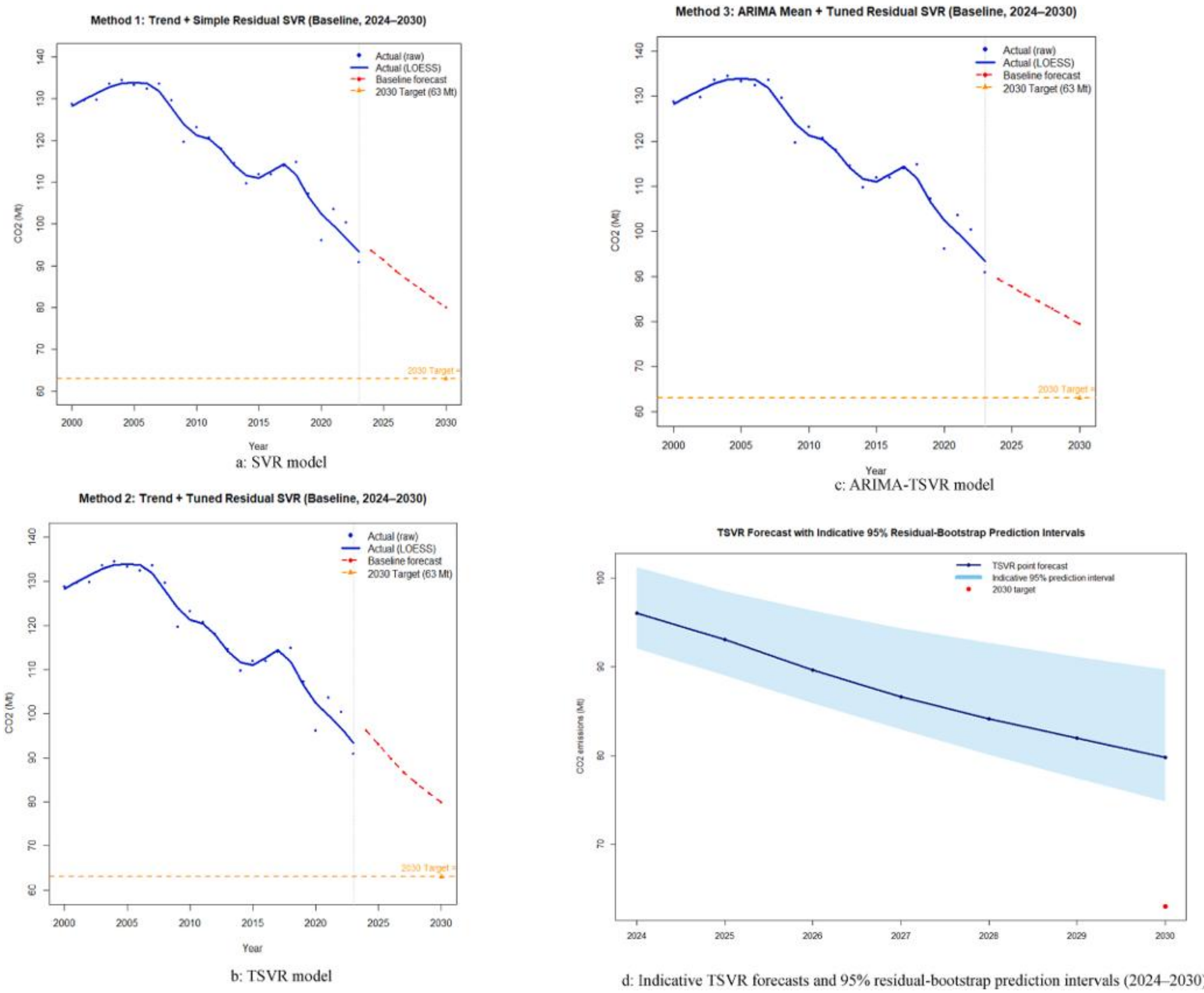


Fig. 4. Forecasted CO_2 emission trajectories and uncertainty assessment using SVR, TSVR, and ARIMA-TSVR models.

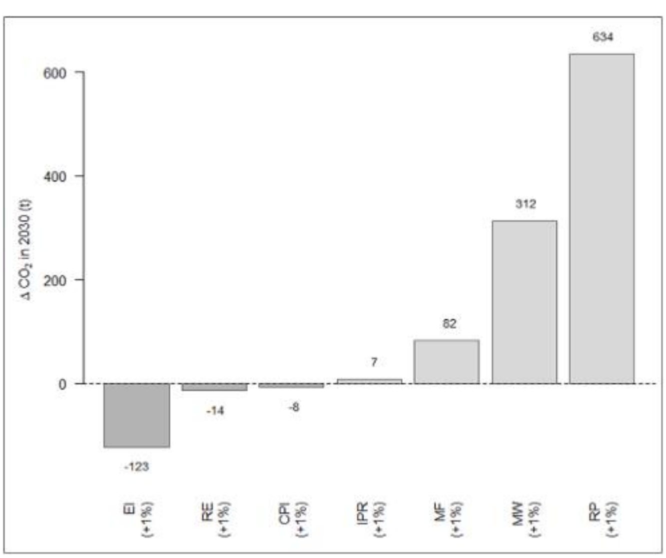


Fig. 5. Contributions to variations in CO_2 emissions.

changes over time and indicating possible long-term consequences for emissions. Circular-economy-related practices, such as resource productivity, emerge as long-term determinants of emissions, as they exhibit comparatively larger adjustments. The lagged dynamic pattern of energy intensity shows an initial short-term reduction followed by an acceleration in the medium to long run, which may signal the presence of a rebound effect. Digitalization exhibits weaker immediate effects but stronger delayed impacts than in the short-run specification.

Furthermore, to address concerns related to sample size and use of aggregated-level data and index construction sensitivity, additional robustness checks are conducted. First, the Pesaran CD test (see Appendix Table A-5) indicates cross-sectional country dependence across countries. Second, the Pesaran CADF and fixed-effect estimation with Driscoll–Kraay standard errors are applied. The results reported in Appendix Tables A-6 to A-8 show that RE, MF, RP, MW, and EI are significantly associated with emissions across countries. Third, the Dumitrescu–Hurlin panel Granger non-causality test results (refer to Appendix Table A-9), which indicate links from explanatory variables to CO_2 emissions. The complementary country-level robustness checks further support the relevance of the main system-level outcomes. In addition, CPI index construction sensitivity check is conducted in Table A-10 in the Appendix. The PCA-based CPI and the alternative

Table 14
Policy adjustments proposed to achieve the 2030 target.

Variables	MW	EI	MF	RE	RP	IPR	CPI
Target by 2030 (%)	−28.86%	−1.29%	−10.13%	19.66%	0.91%	24.88%	0%

Table 15
Causal structure stability (bootstrapping).

Short-run	Node 1	Interaction	Node 2	Ensemble	Edge Sensitivity (Stability)
	lCO_2	→	CO_2	74.01%	Moderate to Strong
	RP	→	CO_2	74.01%	Moderate to Strong
	lIPR	→	CO_2	87.98%	Strong
	lMF	→	CO_2	75.39%	Moderate to Strong
	lRE	→	CO_2	58.74%	Weak
	lCPI	→	CO_2	66.09%	Weak to Moderate
	lEI	→	CO_2	56.52%	Weak
	IPR	→	RP	59.63%	Weak
	MF	→	RP	89.93%	Strong
	lCO_2	→	RP	71.39%	Moderate to Strong
	lMF	→	RP	78.97%	Moderate to Strong
	lMW	→	RP	74.81%	Moderate to Strong
	lRE	→	RP	75.21%	Moderate to Strong
	lRP	→	RP	72.63%	Moderate to Strong
Long-run	Node 1	Interaction	Node 2	Ensemble	Edge Sensitivity (Stability)
	lCO_2	→	CO_2	75.52%	Moderate to Strong
	RP	→	CO_2	72.04%	Moderate to Strong
	lIPR	→	CO_2	87.395	Strong
	lMF	→	CO_2	76.09%	Moderate to Strong
	lRE	→	CO_2	58.36%	Weak
	lCPI	→	CO_2	50.71%	Weak
	IPR	→	RP	40.05%	Weak
	MF	→	RP	52.63%	Weak
	lCO_2	→	RP	71.34%	Moderate to Strong
	lIPR	→	RP	58.84%	Weak
	lMF	→	RP	77.30%	Moderate to Strong
	lMW	→	RP	75.70%	Moderate to Strong
	lRE	→	RP	74.40%	Moderate to Strong
	lRP	→	RP	72.13%	Moderate to Strong

Note: The Ensemble edge sensitivity represents the percentage of bootstrap replications (out of 10,000) in which a given causal edge is retained in the estimated graph. Higher values indicate greater stability of the causal link across repeated samples. The qualitative stability labels are defined as follows: Weak (below 60%); Moderate to Strong (60%-85%); Strong (above 85%).

equal-weighted index show a strong positive correlation ($r = 0.9938$, p-value<0.001, $N = 24$). This suggests that the base CPI index pattern is not sensitive to the weighting method and the results are robust.

The findings have significant implications for various stakeholders involved in the EU decarbonization initiatives. For policymakers, the findings suggest that decarbonization can be achieved through improvement in the dynamic coordination among renewable energy, carbon pricing, circular economy strategies, and digitalization, rather than an isolated enhancement in these instruments. For carbon-market regulators, the results indicate that both emission trading system and carbon pricing mechanisms should be more closely associated with circular economy strategies, in particular resource productivity factor. For firms and industrial sectors, the results highlight the leading role of resource productivity, as well as the importance of improving material efficiency and adopting more cleaner production processes. Finally, the results bring the policymakers' and the ETS regulators' attention to the forecasted trajectories of emissions, which are insufficient to meet the EU's 2030 goals.

6. Conclusion and policy implications

6.1. Conclusion

The EU's 2030 decarbonization roadmap combines ET, DI, CE, and ETS measures to curb emissions and align with the Paris Agreement. Together, these policies enable a comprehensive, system-level examination of CO_2 emission dynamics across European countries. This study seeks to assess whether the EU's 2030 carbon objectives are sufficient for reaching carbon neutrality by examining the contributions of energy intensity, the share of renewable energy, internet penetration, material footprint, resource productivity, municipal waste recycling, and a

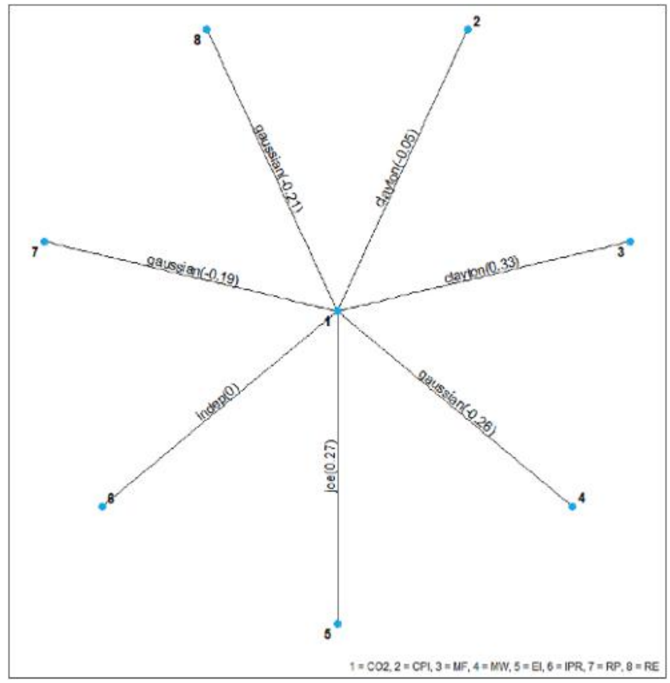


Fig. 6. System-level connectedness structure: CO2 as the central dependence node (Static C-Vine copula).

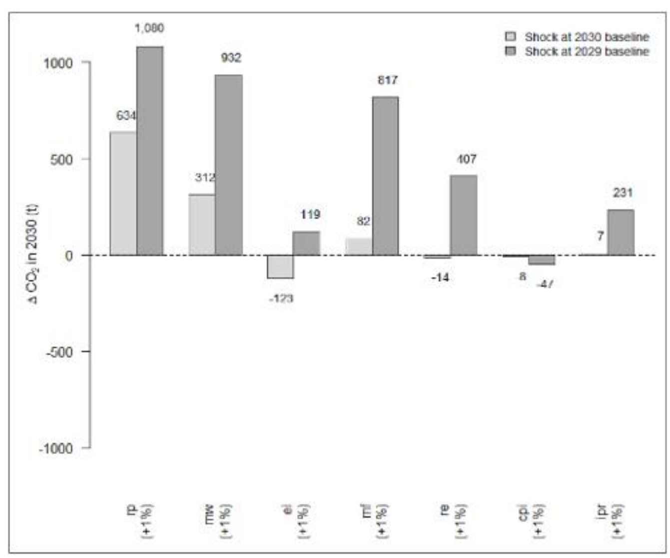


Fig. 7. Robustness check on sensitivity analysis.

carbon policy index (constructed as a linear combination of national and EU-wide emissions trading schemes and carbon taxes). Specifically, the research identifies the underlying causal structure, quantifies the strengths of dependencies, and projects the CO_2 emissions pathway under the EU's climate targets. The analysis advances beyond conventional single-method studies by integrating causal discovery, copula-based dependence modeling, and machine learning–driven forecasting, thereby offering a more holistic understanding of how these factors interact and jointly shape emission outcomes.

Based on the findings, first, the causal model indicates that CO_2 emissions in the EU is not driven by single policy instruments, but by a complex transmission system in which resource productivity emerges as the key mediating factor. Both the contemporaneous and lagged causal structures show that upstream (material footprint) and downstream (municipal waste) elements of the circular economy, together with digitalization, exert their influence on CO_2 emissions indirectly through resource productivity. This implies that resource productivity functions not only as an outcome variable but also as a channel through which policy effects are transmitted. Notably, the persistence of this mechanism in both short- and long-run settings suggests that the EU's decarbonization trajectory is shaped by stable yet intricate interdependencies over time. Second, the time-varying copula-based evidence indicates that the interconnectedness among key drivers is both dynamic and heterogeneous. The magnitude and direction of these dependencies change over time in response to technological progress, policy actions, and macroeconomic disturbances. For example, the linkage between digitalization and CO_2 intensifies during periods of rapid digital expansion but weakens when green digital strategies are implemented. By contrast, the relationship between CO_2 and resource productivity remains consistently negative, though its strength fluctuates over time. These insights question the notion of constant policy effectiveness and indicate that policy impacts are contingent on timing and interaction effects. Third, the forecasting results provide a realistic evaluation suggesting that, although CO_2 emissions in the EU are projected to decline through 2030, this reduction is still insufficient to meet the EU's 55% reduction target relative to 1990. The substantial gap between projected emissions and policy objectives indicates that current policies are working, but not at the speed required. Consequently, the declining trajectory and the remaining policy gap indicate that EU decarbonization is on track but progressing too slowly. Sensitivity analysis corroborates this by showing that strengthening carbon pricing mechanisms helps curb emissions, whereas circular economy initiatives – and resource productivity in particular – can induce rebound or scale effects that partially counteract emission reduction at the margin. Importantly, this finding does not contradict the central role of resource productivity as a transmission channel for decarbonization identified in the causal analysis. Rather, it highlights a fundamental policy design challenge: efficiency improvements that are not accompanied by binding demand-side constraints may stimulate additional economic activity and thus generate offsetting emissions. This implies that circular economy policies must be embedded within a broader regulatory framework that limits aggregate resource consumption, not merely improves its efficiency.

6.2. Policy implications

Building on these results, our study may inform policy measures aimed at meeting the 2030 carbon target through policy reforms. Therefore, it is essential to track these reforms and their effects on CO_2 emissions, as such monitoring can help follow emission trends and assess the effectiveness of climate policies.

The main findings and policy implications of our study are summarized below:

1) The DAG/FASK analysis indicates that DI, ET, ETS, and CE practices function as an interconnected system, rather than as separate policy instruments. In particular, resource productivity functions as a transmission channel, through which MF, MW, RE, and DI transmit their plausible effect to emissions. Therefore, RP should be treated as a central policy objective, rather than merely as a circular economy outcome. Achieving these objectives calls for investments in advanced recycling technologies and green energy policies, along with regulatory incentives that promote more material use across sectors, and determine whether these improvements ultimately reduce emissions. Further analysis highlights that digitalization can be connected to emissions, either directly or indirectly, through mid-stream circular economy practices, while its connection with emissions changes over time. This suggests that EU digital-oriented policies should be more environmentally friendly, while accounting for material efficiency. The EU funding for digital infrastructure may be prioritized for applications that monitor emission reductions, improve material efficiency, and recover waste.
2) The time-varying copula findings show that the strength of the relationship among the driving factors with emissions evolves over time, implying that policy effectiveness is not fixed. A policy that works well in one period may become less effective in another as economic conditions and technologies shift. Consequently, climate policies should be updated periodically, rather than kept unchanged. This can be achieved through regular monitoring of the evolution among the most connected channels, including carbon prices and circular economy strategies in light of their changing relationships over time.
3) Forecasting models project emissions above the 2030 climate goal, with an estimated gap ranging from 16.47 to 17.07 Mt. The EU could establish an annual threshold (based on the policy vs forecast gap) to track whether the EU remains on decarbonization target, rather than waiting until 2030 to evaluate policy success. Annual forecast updates could trigger additional carbon-price adjustments, material-efficiency improvements, energy-efficiency measures or even accelerate digital infrastructures. Therefore, forecasting acts as a policy tool for timely policy action.
4) The sensitivity analysis indicates that implementing improvements in resource efficiency policies may require a comprehensive approach, rather than actions in isolation. Although the practice may support emission reduction through system-level transmission channels, it can also increase production and consumption, and partially offset emission reductions. The policy implication, therefore, is not to abandon circular economy strategies but to design them as part of an integrated package that combines efficiency targets with caps on material throughput and consumption. This action would help policymakers to ensure that improvement in efficiency translates into actual environmental benefits.

6.3. Study limitations

The key limitation of the study is the limited annual series sample (from 2000 to 2023) used in the main system-level analysis. The database of some key variables, including circular economy practices, is limited to the mentioned period. In addition to this, the single regime indicator may not fully capture major shocks such as the Global Financial Crisis and COVID-19 pandemic. Separate event-specific controls are not included in the model because of the limited degree of freedom. Therefore, the findings are interpreted as explanatory evidence and are supported by robustness checks at the country-level. It is worth noting that the country-level panel robustness check employs econometric procedures that differ from the main system-level FASK algorithm, copula models, and SVR analysis; they provide complementary evidence only on associations across countries, not on the specific causal orientations, dependency, and forecasting analysis in the aggregated analysis. Furthermore, the primary analysis of the study is carried out on aggregated system-level series, which does not capture country-specific heterogeneity in circular economy performance, carbon pricing mechanisms, digitalization, energy mix, and economic structure. However, the cross-country-level robustness checks partially address this concern but do not substitute for disaggregated countries.

Future research could extend this study in several directions. First, the use of country-level or sector-level panel data to capture heterogeneity across European economies, in particular in relation to energy transition, carbon pricing mechanism effectiveness, circular economy performance, and digitalization. Second, integration of input-output or embodied-carbon data with dynamic modelling approaches to examine which and how different explanatory variables jointly affect emission. Third, sector-specific and hybrid carbon pricing mechanisms could be examined in more detail, along the lines traced by some recent studies showing that the effectiveness of hybrid ETS and carbon tax may depend on sectoral structure and embodied-carbon transmission channels.

CRediT authorship contribution statement

Parisa Pakrooh: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft. **Matteo Manera:** Conceptualization, Project administration, Supervision, Writing – review & editing.

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Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A-1
Literature review

Author (Year)	Data & Method	Main Finding
Stavins (2007)	• GHG emissions; emissions cap trajectory; allowance allocation; allowance prices; compliance costs; revenue recycling • Policy-oriented analysis	• US-ETS ensures emissions stability, in particular when coupled with international linkage.
Geels (2012)	• Low-carbon transition; socio-technical systems; technology; policy; markets; user practices; infrastructure; cultural and institutional factors. • Multi-level perspective framework	• Low-carbon transitions require long-term co-evolution across technology, policy, markets, and society.
Chen et al. (2021)	• Carbon emission, energy consumption, energy efficiency, renewable energy index • Artificial Intelligence-based useful evaluation model (AIEM)	• Artificial Intelligence overcomes energy efficiency and renewable energy challenges, including client selection, pricing mechanism.
Sen et al. (2021)	• CO_2 emissions; material efficiency; circular economy strategies; renewable energy; energy efficiency; policy incentives • Conceptual and policy analysis	• Circular economy strategies, in particular resources efficiency, enhance decarbonization.
Fang et al. (2021)	• Carbon emissions; carbon intensity; emission trading scheme; emission reduction quotas; marginal abatement costs; allowance allocation schemes; GDP impacts from 2016 to 2030 • Nonlinear programming	• China's ETS reduces abatement cost while achieving dual carbon goals with a peak in 2030.
Yang et al. (2022)	• Total carbon emissions; carbon emission intensity; digital city construction index; technological innovation; industrial structure; energy structure from 2006 to 2019 • Panel regression models	• Digital city reduces CO_2 emissions intensity through innovation and structural transformation, while total emissions follow an inverted U-shape pattern.
Mushafiq and Prusak (2023)	• Resource productivity, material footprint, environmental degradation from 2000 to 2020 • Linear & nonlinear ARDL	• Higher resources productivity reduces environmental degradation, especially in high-material-footprint countries.
Wen et al. (2023)	• Green transition (green total factor productivity, GTFP); carbon emission trading schemes; green technological innovation; productive capital renewal; financing constraints; internal control quality; environmental enforcement intensity from 2010 to 2019 • Staggered difference-in-differences model	• ETS promotes green transition, through green technological innovation.
Zhou (2023)	• Carbon neutrality; energy efficiency; renewable energy; energy storage; energy/carbon trading; building-sector decarbonization; policy instruments • Comprehensive literature review	• Energy efficiency and renewable deployment need to be prioritized in carbon neutrality pathway, which are supported by carbon trading mechanism.
Errendal et al. (2023)	• Carbon pricing (carbon tax, ETS); greenhouse gas emissions; net-zero pathways; electricity sector emissions; food system emissions; policy coverage and price levels from 1990 to 2022 • Policy review and analytical assessment	• Carbon pricing contributes to emission reductions and net-zero pathways but its more effective when combined with complementary policies.
D'Adamo et al. (2023)	• EU allowance (EUA) price; carbon leakage risk; energy futures prices; sustainability criteria; policy alternatives; digital development; circular economy practices	• EU-ETS combination with digitalization, renewable energy, and circular economy policies improve CO_2 reduction.

(continued on next page)

Table A-1 (*continued*)

Author (Year)	Data & Method	Main Finding
	• Long and short-term memory (LSTM) neural network combined with multicriteria decision analysis (MCDA)	
Kurniawan et al. (2023)	• Digitalization technologies (AI, IoT, ML, robotics); waste recycling performance; CO_2 emissions; resource recovery; economic and environmental outcomes • Systematically literature review	• Digitalization facilities improve resource efficiency and recovery in waste recycling and mitigate global CO_2 emissions.
Tian et al. (2023)	• Circular economy practices from 2009 to 2021 • PRISMA-based systematic literature review	• Circular and low-carbon strategies, which mainly depends on energy policies, are mostly complementary.
Cao et al. (2024)	• Agricultural carbon emission intensity; rural digital economy index; agricultural socialized services; economic development; technological investment; fertilizer use from 2010 to 2022 • Entropy method; spatial Durbin model; panel threshold model	• The rural digital economy significantly reduces agricultural CO_2 emissions, specifically through agricultural socialized services.
Li (2024)	• CO_2 emissions; digital transformation; eco-efficiency; natural resource extraction; energy transition; food supply chain; government policy from 1995 to 2022 • Panel econometrics analysis using DOLS, FMLOS, panel Quantile regression, and Dumitrescu–Hurlin panel causality test	• Digital transformation, eco-efficiency, and government policy mitigate CO_2 emissions, while natural resource extraction and energy transition intensify emissions.
Salman et al. (2024)	• Carbon neutrality index; artificial intelligence; Paris Agreement; energy transition; geopolitical risk; green innovation; financial development; industrial structure; foreign direct investment from 1990 to 2022 • Fixed-Effect panel stochastic frontier model with Malmquist index	• Technological advancement and energy transition improve carbon neutrality. AI with the Paris Agreement amplifies carbon neutrality.
Shobande et al. (2024)	• Carbon intensity; emissions trading system (ETS); renewable energy; economic growth; carbon taxes from 2001 to 2019 • Dynamic panel econometric analysis using GMM	• ETS and energy transition expansion reduce CO_2 intensity, while economic growth and carbon tax increase emissions.
Wang et al. (2024)	• CO_2 emissions; circular economy; green logistics; municipal waste generation; GDP; economic growth from 2000 to 2020 • Panel econometric analysis using PMG-ARDL and VECM	• Circular economy and green logistics reduce CO_2 emissions in the long run, while waste generation increase emissions.
Ayub et al. (2024)	• CO_2 emissions; digital economy growth; financial efficiency; economic growth; technological innovation; foreign direct investment; industrialization; energy consumption from 1990 to 2021 • Panel econometrics analysis using AMG and Dumitrescu–Hurlin panel causality test	• Digital economy development and financial efficiency reduce CO_2 emissions, while economic growth, energy consumption, and industrialization increase emissions.
Li et al. (2024)	• Carbon neutrality; renewable energy consumption; green taxes; trade openness; financial globalization; efficient resource management; population growth from 1990 to 2021 • Panel econometric analysis using FMOLS estimator	• Renewable energy consumption and green taxes enhance carbon neutrality, while trade openness and financial globalization show heterogenous effects across emission levels.
Yao et al. (2024)	• CO_2 emissions; industrial robot adoption; economic growth; technological progress; structural transformation; energy intensity from 1993 to 2015 • Panel econometric analysis	• Industrial robot adoption reduces CO_2 emissions, mainly through economic growth and technological progress affects.
Jamasb et al. (2024)	• Economic growth; net-zero carbon emissions; circular economy; capital accumulation; pollution; recycling • Analytical growth model	• Circular economy is necessary condition for achieving net-zero emissions alongside economic growth, and active environmental policies.
Tang et al. (2024)	• CO_2 emissions; energy structure; coal consumption; industrial pollution control investment; ETS policy; Coal Control and Clean Utilization (CCCU); Green Financial Reform and Innovation Pilot Zone (GFPZ) from 2006 to 2020 • Difference-in-differences (DID) models	• ETS, CCCU, and GFPZ policies reduce emissions and promote energy transition. However, policy interaction shows both interactions and conflicts depending on policies combinations.
Evro et al. (2024)	• Carbon neutrality strategies; greenhouse gas emissions; renewable energy transition; carbon capture technologies (CCS/CCUS); circular economy; policy frameworks • Systematic and comparative literature review with multidimensional policy analysis	• The EU shows the most comprehensive policy framework, while the US and China rely more on domestic policy heterogeneity and international coordination to achieve global carbon neutrality.
Prapaspongsa et al. (2024)	• GHG emissions (CO_2e); municipal waste; circular economy scenarios; waste separation; recycling rates; income-level–specific waste systems from 2023 to 2050 • Life-cycle assessment analysis (LCA)	• Current waste management emits substantial GHGs. Circular economy strategies can significantly reduce emissions in the waste sector by 2030-2050.
Bibri et al. (2024)	• Artificial intelligence; AIoT; urban digital twin; data-driven urban planning; environmental sustainability; smart city systems from 2019 to 2023 • PRISMA-based systematic literature review	• The synergistic integration of AI, AIoT, and urban digital twins improves environmental sustainability, resource efficiency, and CO_2 reduction.
Kumar et al. (2024)	• Circular economy performance; Industry 5.0 technologies; digital technologies (AI, IoT, big data, CPS); sustainability; resilience; human-centered manufacturing • Expert survey combines with fuzzy analytical hierarchy process (FAHP)	• Digitalization support circular economy implementation in Industry 5.0 with AI, data, and human-centered technologies prioritized for sustainable manufacturing.
Wang et al. (2024)	• Carbon emission efficiency (CEE); energy consumption; gross regional product; population size; urban area; technological innovation; electricity consumption; urban greening from 2006 to 2020 • SBM directional distance function (SBM-DDF) combine with machine-learning algorithms	• Energy consumption is the dominant driver of carbon emissions, while technology and greening matter more in low-carbon-growth cities.
Zhang et al. (2024)	• Carbon emissions; carbon taxes; emissions trading systems; policy design features; economic impacts; complementary climate policies • Comprehensive global literature review	• Both carbon taxes and ETS reduce emissions, but integrated policy frameworks combining with complementary measures are more effective.
Liu et al. (2024)	• Energy transition index; carbon emission trading scheme (ETS); technological innovation; financial decarbonization; energy structure; provincial controls from 2010 to 2016 • Difference-in-differences (DID) combines with propensity score matching (PSM)	• China's ETS promotes energy transition through technological innovation and financial decarbonization channels.

(*continued on next page*)

Table A-1 (*continued*)

Author (Year)	Data & Method	Main Finding
Ai et al. (2024)	• Collaborative reduction of pollutant and carbon emissions (CRPC); digital inclusive finance; technological effect; electrified energy mix; environmental regulation; control variables from 2011 to 2020 • Spatial Dublin Model	• Digital finance reduces CO_2 emissions with strong spatial spillover effect through technological progress and energy transition.
Shi et al. (2024)	• Carbon emissions; digital economy index; regional economic development; energy consumption; coupling coordination degree from 2005 to 2020 • Multiple regression analysis combines with system dynamic modeling	• The relationship between the digital economy and CO_2 emissions follows an inverted U-shape.
Foggia et al. (2024)	• ETS efficiency, SDG indicators, circular economy variables from 2016 to 2021 • Panel data analysis	• EU-ETS improves environmental taxation efficiency and reduce climate-related economic losses.
Deng et al. (2025)	• Carbon emission reductions; solid waste generation intensity; waste utilization rate; treatment structure; disposal methods; emission intensity from 2018 to 2020 • Carbon accounting framework for solid waste management processes combines with Logarithmic Mean Divisia Index (LMDI) decomposition analysis	• The Zero-waste City program reduces CO_2 emissions by controlling waste generation intensity and improving the structure, with emission intensity as the key driver.
Wang et al. (2025)	• Carbon emission reduction; green finance index; digital economy index; green technological innovation; population size; regional heterogeneity controls from 2010 to 2022 • Panel econometric analysis	• Both green finance and digital economy reduce CO_2 emissions through green technological innovation.
Maftei et al. (2025)	• Digitalization, renewable energy consumption, GHG emissions from 2000 to 2021 • Panel model analysis using GMM and PCSE	• Digitalization has a mixed direct effect on emissions, while indirectly reduce GHG emissions through renewable energy, green digitalization is crucial for climate benefits.
Lu et al. (2025a)	• Carbon tax, ETS, embodied carbon, building sector and energy industries • CGE model and micro-Sam table	• Hybrid carbon tax-ETS policies can reduce emissions in the building sector.
Lu et al. (2025b)	• ETS, differentiated carbon tax, construction sector, industry linkage, environmental indicators, energy • CGE model with nine policy scenarios and micro-SAM table	• Combining ETS with a differentiated carbon tax performs better than combining ETS with a uniform carbon tax on emission reduction in the construction sector.

Sources: Authors elaborations

Table A-2
Data sources

Data (unit)	Source
Annual CO_2, emissions	https://ourworldindata.org/CO2-emissions
GDP	https://ourworldindata.org/grapher/gdp-worldbank-constant-usd
Primary energy consumption	https://ourworldindata.org/grapher/energy-intensity-of-economies?tab=line
Energy Intensity	Calculated by Authors
Renewables	https://ec.europa.eu/eurostat/databrowser/view/nrg_ind_ren/default/table?lang=en
Denmark carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Estonia carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
EU-ETS	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Finland carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
France carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Germany ETS	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Latvia carbon Tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Luxembourg carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Netherlands carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Norway carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Poland carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Portugal carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Slovenia carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Spain carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Sweden carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Switzerland carbon tax	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Switzerland ETS	https://carbonpricingdashboard.worldbank.org/compliance/revenue
Material Footprint	https://ec.europa.eu/eurostat/databrowser/view/cei_pc020_custom_18969887/default/table
Resource Productivity	https://ec.europa.eu/eurostat/databrowser/view/cei_pc030_custom_18970319/default/table
Municipal waste recycled	https://ec.europa.eu/eurostat/databrowser/view/cei_pc031_custom_18973123/default/table
Share of the population using the internet	https://ourworldindata.org/grapher/share-of-individuals-using-the-internet

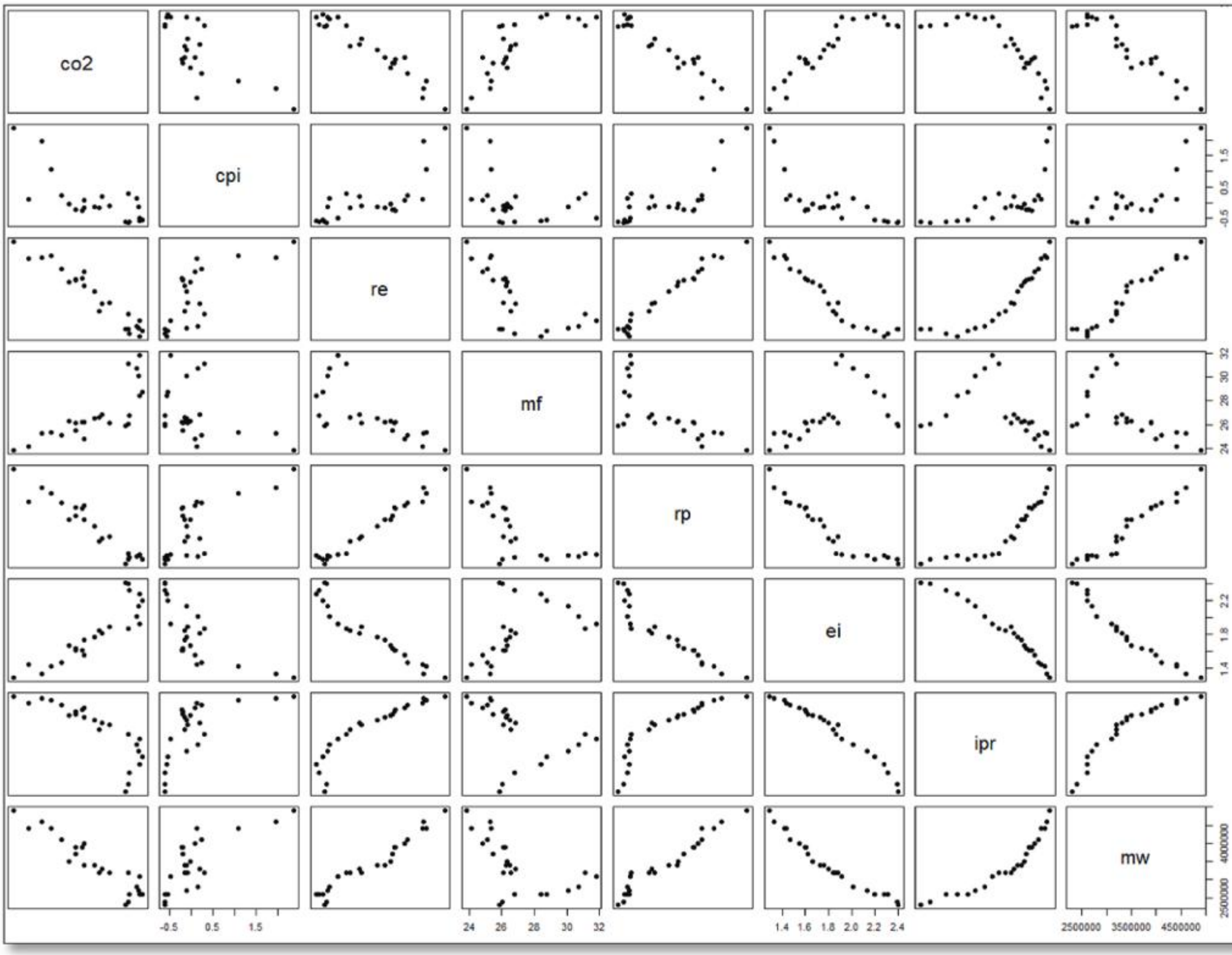

Fig. ure A-1. Scatterplot matrix.

Table A-3
Correlation matrix

	CO_2	CPI	RE	MF	RP	MW	EI	IPR
CO_2	1							
CPI	−0.71	1						
RE	−0.96	0.70	1					
MF	0.81	−0.39	−0.74	1				
RP	−0.96	0.73	0.98	−0.77	1			
MW	−0.94	0.76	0.97	−0.66	0.97	1		
EI	0.90	−0.70	−0.96	0.59	−0.93	−0.97	1	
IPR	−0.85	0.63	0.92	−0.55	0.89	0.92	−0.98	1

Table A-4
Comparison of the average forecast errors

Model	RMSE	MAE	MAPE
Linear	4560771	3553956	3.21
Radial	4312189	3125054	2.83
Polynomial	9796628	8282527	7.28

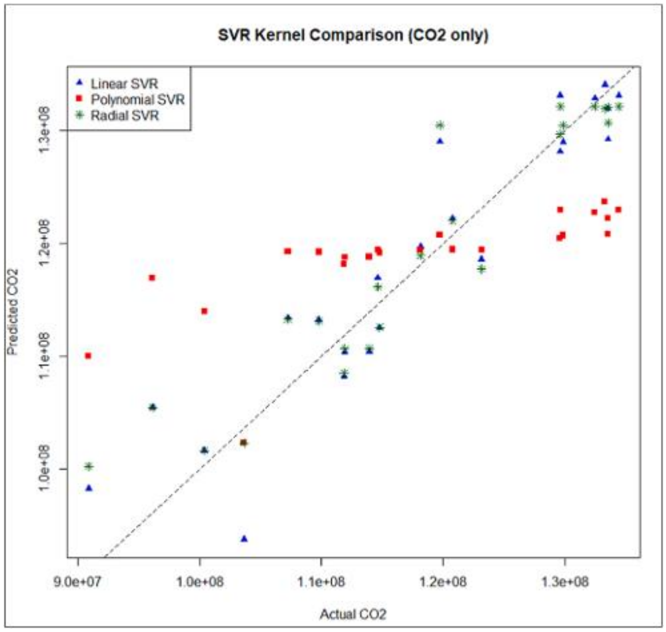

Fig. ure A-2. SVR kernel comparison.

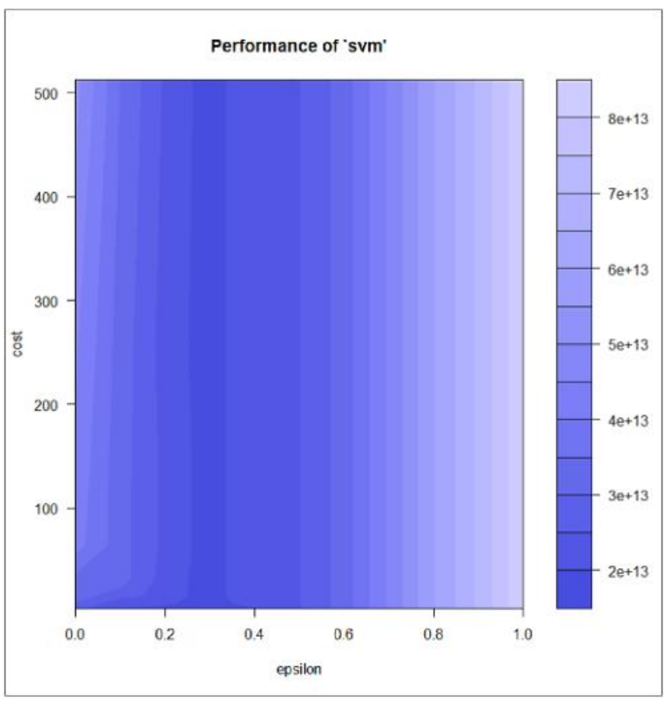

Fig. ure A-3. Hyperparameter performance map - TSVR model.

Table A-5
Cross-sectional dependence test: Pesaran CD test

Variable	Test	CD-test	p-value	corr	abs(corr)	conclusion
$lnCO_2$	Pesaran CD	19.86	(0.00)	0.22	0.28	Cross-Sectional Dependence
lnRE	Pesaran CD	9.29	(0.00)	0.10	0.24	Cross-Sectional Dependence
lnMF	Pesaran CD	22.15	(0.00)	0.25	0.28	Cross-Sectional Dependence
lnCPI	Pesaran CD	78.83	(0.00)	0.89	0.89	Cross-Sectional Dependence
lnRP	Pesaran CD	9.34	(0.00)	0.10	0.20	Cross-Sectional Dependence
lnMW	Pesaran CD	3.52	(0.00)	0.04	0.18	Cross-Sectional Dependence
lnIPR	Pesaran CD	46.81	(0.00)	0.53	0.53	Cross-Sectional Dependence
lnEI	Pesaran CD	15.66	(0.00)	0.17	0.26	Cross-Sectional Dependence

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A-6
Panel stationary tests (Pesaran CADF test)

Variable	Test	Deterministic	Lag	t-bar	Z[t-bar]	p-value	conclusion
$lnCO_2$	Pesaran CADF	Constant	1	−4.001	−11.93	(0.00)	Stationary at levels
lnRE	Pesaran CADF	Constant	1	−3.69	−10.29	(0.00)	Stationary at levels
lnMF	Pesaran CADF	Constant	1	−3.38	−8.65	(0.00)	Stationary at levels
lnCPI	Pesaran CADF	Constant	1	−2.88	−6.00	(0.00)	Stationary at levels
lnRP	Pesaran CADF	Constant	1	−3.44	−8.45	(0.00)	Stationary at levels
lnMW	Pesaran CADF	Constant	1	−3.09	−7.14	(0.00)	Stationary at levels
lnIPR	Pesaran CADF	Constant	1	−4.60	−2.30	(0.00)	Stationary at levels
lnEI	Pesaran CADF	Constant	1	−3.55	−9.58	(0.00)	Stationary at levels

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A-7
Additional long-run co-movement checks

Kao test for cointegration (H0: No cointegration)	Statistics	p-value
Modified Dickey–Fuller t	−32.21***	(0.00)
Dickey–Fuller t	−27.75***	(0.00)
Augmented Dickey–Fuller t	−18.56***	(0.00)
Unadjusted modified Dickey–Fuller t	−37.75***	(0.00)
Unadjusted Dickey–Fuller t	−28.02***	(0.00)
Pedroni test for cointegration (H0: No cointegration)	Statistics	p-value
Modified Phillips–Perron t	4.29***	(0.00)
Phillips–Perron t	−14.03***	(0.00)
Augmented Dickey–Fuller t	−13.45***	(0.00)
Westerlund test for cointegration (H0: No cointegration)	Statistics	p-value
Variance ratio	1.38*	(0.08)

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A-8
A country-level FE model using Driscoll–Kraay standard errors

$lnCO_2$	Coefficient	Driscoll–Kraay SE	t	p-value
lnRE	−0.10**	0.04	−2.06	(0.05)
lnMF	0.10**	0.04	2.39	(0.02)
lnCPI	0.09	0.08	1.07	(0.29)
lnRP	−0.10**	0.04	−2.34	(0.02)
lnMW	0.05**	0.02	2.07	(0.05)
lnIPR	0.007	0.03	0.03	(0.98)
lnEI	0.16***	0.02	6.03	(0.00)
D	−0.45	0.35	−1.29	(0.21)
F-test	15.88*** (0.00)			
OBS	594			
Groups	27			

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A-9
Dumitrescu and Hurlin (2012) Granger non-causality test results

Null Hypothesis	Lag	W-bar	Z-bar (p-value)	Z-bar tilde (p-value)
H0: lnRE does not Granger-cause $lnCO_2$	1	1.74	2.73 (0.00)***	1.83 (0.06)*
H0: lnMF does not Granger-cause $lnCO_2$	1	2.41	5.21 (0.00)***	3.83 (0.00)***
H0: lnCPI does not Granger-cause $lnCO_2$	1	2.08	3.98 (0.00)***	2.84 (0.00)***
H0: lnRP does not Granger-cause $lnCO_2$	1	1.74	2.72 (0.00)***	1.83 (0.06)*
H0: lnMW does not Granger-cause $lnCO_2$	1	1.06	0.24 (0.80)	−0.17 (0.80)
H0: lnIPR does not Granger-cause $lnCO_2$	1	1.36	1.35 (0.17)	0.72 (0.46)
H0: lnEI does not Granger-cause $lnCO_2$	1	1.40	1.50 (0.13)	0.84 (0.39)
H0: lnRE does not Granger-cause $lnCO_2$	2	2.61	1.60 (0.10)*	0.59 (0.54)
H0: lnMF does not Granger-cause $lnCO_2$	2	3.70	4.42 (0.00)***	2.68 (0.00)***
H0: lnCPI does not Granger-cause $lnCO_2$	2	2.59	1.54 (0.12)	0.55 (0.57)
H0: lnRP does not Granger-cause $lnCO_2$	2	3.62	4.22 (0.00)***	2.54 (0.01)***
H0: lnMW does not Granger-cause $lnCO_2$	2	1.06	0.24 (0.80)	−0.17 (0.86)
H0: lnIPR does not Granger-cause $lnCO_2$	2	4.43	6.32 (0.00)***	4.09 (0.00)***
H0: lnEI does not Granger-cause $lnCO_2$	2	2.91	2.37 (0.01) ***	1.17 (0.24)

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A-10
PCA construction of the Carbon Policy Index

Components	PC1 weight
National ETS	0.5781
EU-ETS	0.5285
National carbon tax	0.6216
Eigenvalue of PC1	1.3131
Variance explained	43.77%

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A-11
Robustness checks using separate carbon-pricing indices and Driscoll–Kraay standard errors

Variable	Baseline CPI	ETS-only	Carbon-tax-only
lnRE	−0.10**	−0.102**	−0.101**
lnMF	0.10**	0.118*	0.119*
CPI	0.09	0.048	0.077
lnRP	−0.10**	−0.08**	−0.078**
lnMW	0.05**	0.047*	0.047*
lnIPR	0.007	0.002	0.005
lnEI	0.16***	0.16***	0.156***
D	−0.45	−0.447	−0.416
OBS	594	594	594
Groups	27	27	27
F-test	15.88***	22.41***	18.47***

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels.

Table A-12
Sensitivity check for the construction of the CPI index

CPI index	Correlation	p-value	OBS
PCA-based CPI and Equal-weighted CPI	0.9938	(0.00)***	24

Data availability

Data will be made available on request.

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