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ORIGINAL PAPER

Tax, Tech, and Trash: Synergies in Circular Economy Transitions

Siamand Hesami[1]

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Abstract
This study examines how fiscal and technological factors jointly shape recycling performance within the circular economy framework. Using a balanced panel of eight European Union countries from 2010 to 2024, the analysis integrates System GMM, Fixed-Effects, and Stochastic Frontier Analysis to assess the interaction between landfill taxation and technological efficiency. The results show that the association between landfill taxes and recycling rates strengthens significantly with higher levels of technological efficiency, indicating that technology enhances the effectiveness of fiscalinstruments rather than acting independently. Recycling rates also display strong path dependency, suggesting that historical performance and institutional continuity play a central role in shaping current outcomes. The findings refine Pigovian and ecoinnovation perspectives by demonstrating that fiscal measures are most effective when aligned with technological and institutional capacity. Overall, the study provides empirical evidence that integrating fiscal policy with technological advancement can accelerate progress toward circular economy objectives under the European GreenDeal.

Introduction

The global transition to a circular economy, characterised by the systematic reuse of resources and waste minimisation, has become an urgent priority in addressing the escalating waste crisis, projected to reach 3.4 billion tonnes annually by 2050 [1]. Within Europe, this shift is exemplified by diverse national strategies: Belgium employs substantial landfill taxes to incentivise recycling, Germany leverages advanced technological systems to achieve high recycling rates, and Sweden integrates incineration for energy recovery while maintaining strong recycling programs, though some argue this may reduce incentives for material recycling. These varying approaches among countries provide a rich context for examining the mechanisms driving circular economy outcomes, particularly recycling rates. This study investigates the interplay between landfill taxes, environmental tax revenues, and technological advancements, addressing a critical research question: how do these fiscal and

✉ Siamand Hesami
shesami@bournemouth.ac.uk

1 Bournemouth University Business School, Poole, England

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technological factors synergise to enhance recycling rates, and what explains the observed heterogeneity across nations?

The theoretical foundation for this inquiry rests on integrating fiscal policy and technological innovation as dual drivers of environmental sustainability. Based on Pigou's [2] externality pricing framework, landfill taxes internalise environmental costs to promote recycling. Studies confirm their effectiveness in reducing landfill waste and increasing recycling rates [3]. Environmental tax revenues, similarly, are designed to fund systemic improvements and influence waste management behaviours by internalising environmental costs and incentivising sustainable practices [4]. Alongside, technological advancements, ranging from widespread adoption of recycling methods to efficiency-driven innovations in material recovery, offer practical solutions for closing resource loops, aligning with the circular economy principles outlined by the Ellen MacArthur Foundation [49]. Economic theory suggests that taxation and technology should function synergistically: taxes create financial incentives and generate resources for investment, while technologies enhance their effectiveness by enabling sustainable practices. However, empirical evidence reveals inconsistencies, some nations achieve high recycling rates without heavy reliance on landfill taxes (e.g., Germany). In contrast, others with robust fiscal measures exhibit moderate outcomes (e.g., the Netherlands), suggesting a complex interplay that warrants deeper analysis.

Significant gaps persist despite a growing body of literature on circular economy transitions. Studies have explored the individual impacts of landfill taxes (e.g., Jofre-Monseny and Sorribas-Navarro [3]; Panzone, et al. [5]) and technological adoption (e.g., Fatimah, et al. [6]; Seyyedi, et al. [7]) on waste management, yet few have systematically examined their synergistic effects across a multi-country panel, warranting further research. Moreover, the role of recycling rate persistence, where past performance influences current outcomes, and its interaction with fiscal and technological factors remains underexplored. This study addresses these lacunae by employing a robust econometric approach, combining the System Generalised Method of Moments (GMM) and fixed effects model analysis of a balanced panel of eight European countries.

The contributions of this research are threefold, advancing both theoretical and empirical frontiers in the field of circular economy scholarship. First, it quantifies the long-term effects of landfill taxes and environmental tax revenues on recycling rates, accounting for dynamic persistence, an aspect often overlooked in prior work. By revealing the sustained influence of historical recycling performance, this study offers a novel perspective on path dependency in waste management systems. Second, it identifies and tests a critical synergy between landfill taxes and technological efficiency, moving beyond the standalone effects of technological adoption to highlight efficiency as a pivotal amplifier of fiscal policy impact. This finding refines Pigovian and innovation diffusion theories [8], providing a more nuanced understanding of how these factors converge. Third, it explains the role of national contexts in mediating circular outcomes, offering comparative insights across countries with diverse waste management strategies, thus enriching the application of the Environmental Kuznets Curve and institutional theory in this domain.

This analysis spans Belgium, Denmark, Germany, France, Italy, the Netherlands, Austria, and Sweden, leveraging landfill tax data and a novel measure of technological efficiency to examine these dynamics from 2010 to 2024. The findings enhance understanding of circular economy mechanisms within this European context and yield broader implications for global policy design and sustainability efforts. As the European Union's Circular Economy

Action Plan [9] promotes accelerated transitions, this study provides a timely and rigorous framework for policymakers and scholars, highlighting how fiscal tools and technological efficiency are utilised to advance circularity across diverse national landscapes.

Figure 1 illustrates the divergent trajectories of municipal recycling rates across eight European countries from 2010 to 2024, highlighting the heterogeneity this study seeks to explain.

Theoretical and Empirical Background

The pursuit of circular economies, where resources cycle endlessly rather than being wasted, has evolved over the past century, shaped by economic principles, environmental imperatives, and policy ingenuity, with renewed vigour in contemporary research [10, 11]. This study's exploration of how landfill taxes and technological advances synergies to bolster recycling rates, a cornerstone of circularity, arises from a vibrant intellectual tradition spanning classical economics to modern sustainability science, as underscored by recent calls for holistic waste management approaches [12–14].

The roots of this investigation can be traced back to Pigou's [2] seminal treatise on externalities, which advocated for the use of taxes to offset societal costs, such as waste and pollution. This Pigovian perspective matured through the 20th century, with Baumol and Oates [15] refining fiscal instruments to curb environmental harm, paving the way for Europe's embrace of environmental taxes by the 1990s. Belgium and Denmark's early landfill tax schemes exemplified this shift, positioning such levies as potential drivers of recycling rates, a key focus here. However, empirical studies challenge the standalone effectiveness of waste taxation. Mazzanti and Zoboli [16] found that while European waste taxes reduced waste generation, they had a limited impact on boosting recycling. Thus, modern tax policies designed to support a circular economy, including environmental taxes and tax expenditure schemes, often necessitate broader fiscal reforms and complementary incentives to effectively drive circular practices such as reuse and recycling [17, 18].

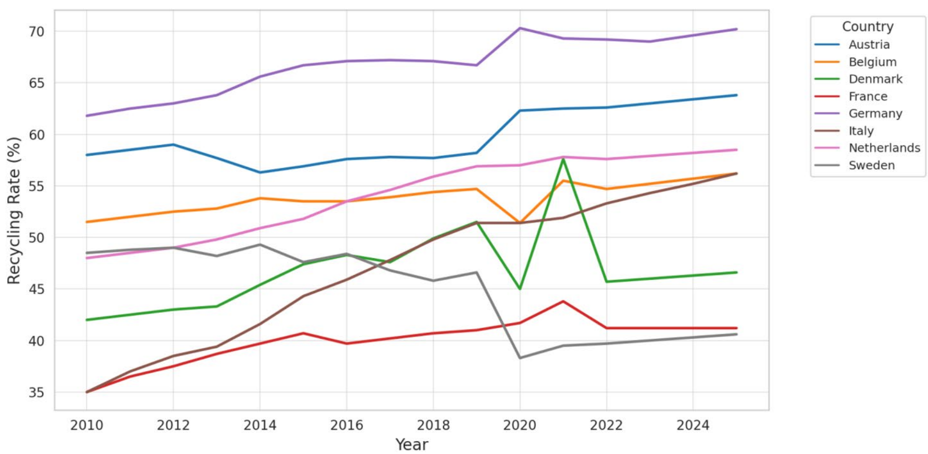

Fig. 1 Trends in municipal recycling rates (% of total municipal waste)

Parallel to this fiscal evolution, technological innovation emerged as an economic force, tracing its lineage to the concept of creative destruction [19] and diffusion of innovations [8], which argues that targeted technologies transform systems when aligned with societal aims. The environmental crises of the 1970s shifted the focus toward sustainability, with Germany pioneering recycling technologies by the 1980s to manage its growing waste. This trajectory solidified within the circular economy framework (EMF, 2012), spotlighting investments in recycling infrastructure as a crucial lever, another focal point of this study. Recent scholarship supports this: Anas, et al. [20] and Zink and Geyer [21] demonstrate that technological investments directly enhance recycling rates, while Zhang, et al. [22] highlight how advanced waste systems propel European circularity, framing technology as a dynamic driver of this process.

The nexus of fiscal and technological strategies gained analytical depth with the Environmental Kuznets Curve (EKC) hypothesis [23], positing that environmental degradation peaks before declining as economies adopt cleaner technologies. Europe's waste policies since the 2000s have tested this arc, with Germany's high recycling rates marking an EKC inflexion point. At the same time, Sweden's reliance on incineration and Austria's balanced approach suggested earlier stages or divergent paths. Although technological investments have boosted EU recycling [24], a trend affirmed by Ghisellini, et al. [25], national contexts have mediated outcomes, foreshadowing this study's emphasis on country-specific effects.

The 2010s ushered in a pivotal shift as the EU's Circular Economy Action Plan [26] urged the integration of tax and technology, with Germany's Circular Economy Act (BMUV, 2012) channelling revenues into recycling, Sweden balancing fiscal incentives with energy recovery, and Belgium leveraging steep landfill taxes. Nevertheless, gaps persisted.

While landfill taxes and Pay-As-You-Throw (PAYT) schemes have effectively increased recycling rates, their success varies depending on pre-existing waste management infrastructure and local economic conditions. For example, in Catalonia, a landfill tax ranging from €18 to €47 per tonne has led to a 6 per cent increase in recycling rates [3]. Similarly, a PAYT system in Ferrara, Italy, improved recycling from 38.2% to 58.9%, a 40-percentage point increase [27]. However, some studies indicate that taxation alone may not always be sufficient. Banacu, et al. [28] claim that environmental taxes (including landfill taxes) had a statistically significant but negative impact on recycling rates across 27 EU countries, suggesting the need for complementary incentives. Their study highlights the importance of careful tax design and the potential need for tailored approaches in different contexts.

Furthermore, Pfister and Mathys [29] observed that the reduction in unsorted waste after implementing a waste tax was not fully compensated by increased recycling, indicating that environmental taxes may lead to broader changes in consumer behaviour, potentially reducing overall waste generation. This suggests that increasing environmental taxes alone does not necessarily lead to higher recycling rates and may, in some cases, act as a barrier to investment in recycling initiatives. This aligns with broader calls for a holistic approach integrating economic, technological, and regulatory measures to advance circular economy principles [30]. Tisserant, et al. [31] suggest fiscal policies often fund infrastructure rather than shift behaviour outright and highlight how waste treatment investments, particularly in high-income countries, have led to improvements in recycling infrastructure, energy recovery, and landfill management. Kirchherr, et al. [32] and Hartley, et al. [33] argue that technological advancements outpace tax incentives in circular progress, a tension that this study's findings resolve by revealing a synergy between landfill taxes and technological efficiency, where raw adoption alone proves less effective.

Institutional theory [34] enriched this discourse by framing national policies and infrastructures as shapers of circular success. Germany's regulatory framework contrasts with Sweden's focus on incineration and the Netherlands' pragmatism, a divergence that Milios [11] attributes to institutional legacies, a precursor to the country's effects. As global waste approached 2 billion tonnes annually [35], recent appeals by Horbach and Rammer [36] for integrated models, merging fiscal, technological, and contextual factors, gained traction, noting that national heterogeneity (e.g., Germany's high waste volumes compared to Austria's smaller scale) demands nuanced scrutiny.

This study emerges at this crossroads, propelled by a century of theory, from Pigou's fiscal remedies to Schumpeter's technological dynamism, refined by the EKC's developmental lens and institutional nuance, and fortified by recent evidence that aligns with our results. The significant persistence of recycling rates reflects path dependency (EMF, 2012), while the long-term effect of landfill taxes and their synergy with technological efficiency refine insights into Pigovian taxes and innovation diffusion [37]. The broader influence of environmental tax revenues suggests indirect funding roles [16], and country variations align with institutional theory [34]. The research question of how landfill taxes and technological advances synergise to enhance recycling rates and why outcomes vary across countries addresses unresolved debates: the direct versus indirect impacts of taxes, the catalytic role of technology, and national mediation. Our model, which tests these dynamics across eight nations with recycling rates as the outcome, bridges historical foundations with contemporary imperatives, advancing both circular economy scholarship and practice.

Data and Methodology

This study employs a balanced panel dataset spanning eight European countries, Belgium (BE), Denmark (DK), Germany (DE), France (FR), Italy (IT), Netherlands (NL), Austria (AT), and Sweden (SE), from 2010 to 2024. Data are sourced from Eurostat, the OECD Patent Database, the World Bank, and national statistical reports. Table 1 defines the variables, their units, and sources, while Table 2 presents descriptive statistics derived directly from the dataset.

While most indicators are sourced directly from Eurostat, the OECD Patent Database, and national statistical reports, official 2024 data were not fully available for all variables at the time of analysis. Accordingly, the 2024 observations were constructed using country-specific linear projections based on the preceding three-year trends (2021–2023). This method preserves the direction and scale of national trajectories while avoiding discontinuities in the balanced panel.

To test the robustness of this approach, all models were re-estimated excluding the projected year (up to 2023), yielding consistent coefficients and significance levels. The synergy between landfill taxation and technological efficiency remained positive and significant, confirming that the results are not sensitive to the inclusion of the projected 2024 data.

The dependent variable, Recycling Rate, measures the percentage of municipal waste recycled, ranging from 35% (France and Italy at 2010) to 70.3% (Germany at 2020), reflecting diverse national performances. Landfill Tax captures the tax levied on landfill disposal,

Table 1 Variable definitions and sources

Variable	Definition	Unit	Source
Recycling Rate	Percentage of municipal waste recycled	%	Eurostat
Landfill Tax	Tax levied on landfill disposal of waste	€/tonne	National reports
Recycling Subsidies	Subsidies provided for recycling activities	€/tonne	National reports
Tech Adoption	Number of waste-related patent counts	Count	OECD Patent Database
Environmental Tax	Environmental tax revenue as a share of GDP	% of GDP	Eurostat
Circular Investment	Investment in circular economy initiatives	€ million	EU funding data
Waste Generation	Municipal waste generated	Thousand tonnes (kt)	Eurostat
GDP Per Capita	Economic output per person	€	World Bank
Technological Efficiency	Log of the ratio of recycling output to tech input	Log value	Derived
Waste Treated	Total waste treated (including municipal, industrial, and other streams)	Million tonnes (Mt)	Eurostat

Table 2 Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Recycling Rate	52.81	9.71	35.00	70.30
Landfill Tax	47.77	47.14	0.00	140.00
Recycling Subsidies	16.77	11.42	0.00	40.00
Tech Adoption	111.11	77.91	5.00	314.80
Environmental Tax	2.52	0.64	1.62	4.14
Circular Investment	9.34	8.06	1.64	34.49
Waste Generation	579.27	127.03	366	918
GDP Per Capita	41,322	9,248	26,880	68,864
Technological Efficiency Log	2.03	0.72	0.61	3.87
Waste Treated	137.89	131.05	13.65	383.20

Circular Investment in € million; Waste Generation in thousand tonnes; Waste Treated in million tonnes; GDP Per Capita in €

with variations such as the Netherlands' increase from €0 (2012–2014) to €33.15 (2021–2024) and Germany's consistent rate of €0 due to landfill bans, as reported by national sources. Waste Treated integrates Eurostat's waste treatment data, encompassing all waste streams (municipal, industrial, and others), with interpolations for odd years (e.g., Belgium 2011: 38.02 million tonnes). The Technological Efficiency serves as a proxy for recycling efficiency per patent, addressing the effectiveness of technological input. Other variables, Recycling Subsidies, Tech Adoption, Environmental Tax, Circular Investment, Waste Generation, and GDP Per Capita, are compiled from their respective sources, including Eurostat, OECD Patent Database, World Bank, and EU funding data, providing a comprehensive foundation for the analysis.

As the study integrates data from multiple international sources (Eurostat, OECD, and the World Bank), a systematic harmonisation process was implemented to ensure consistency across definitions and measurement units. Eurostat served as the reference framework for variable definitions and units. OECD indicators, particularly those related to environmental patents and technological development, were converted to the same annual structure and scaled to a per-capita basis where applicable. World Bank indicators such as GDP per capita were cross-checked against Eurostat values to confirm consistency.

All indicators were expressed in comparable units (e.g., €/tonne, percentage of GDP, or per capita euros) and aligned to a uniform 2010–2024 time series. Where discrepancies in timing or reporting were identified, data were adjusted using linear interpolation to maintain temporal continuity. In addition, outlier values were winsorised at the 1st and 99th percentiles to reduce the influence of exceptional observations. These steps ensured that the combined dataset is internally consistent and suitable for panel econometric analysis.

Table 2 reveals the descriptive statistics, showcasing a landscape of striking variation across the sample. The aggregated means mask substantial variation across countries: recycling rates vary between modest gains in countries like France and Italy and notable achievements in Germany, hinting at deep-seated policy and infrastructural disparities. Landfill taxes illustrate a spectrum from negligible to punitive, concealing divergent fiscal philosophies, while circular investments, ranging from modest increments to substantial commitments, indicate uneven progress toward circularity. Waste generation and treatment volumes further highlight this heterogeneity, with smaller countries like Denmark contrasted against industrial giants like Germany, reflecting not just scale, tempered by data nuances, but also suggesting the subtle interplay of economic development and waste management priorities that influence the trajectory of the circular economy.

To capture the efficiency of technological adoption in enhancing recycling outcomes, this study derives a technological efficiency metric, defined as the ratio of recycling output (Recycling Rate × Waste Generation) to technological input (Tech Adoption), log-transformed to normalise its distribution and facilitate interaction analysis. The Technological Efficiency Log builds on eco-innovation literature (e.g., Horbach [37]; Nicolli, et al. [38]), which emphasises efficiency over raw adoption and is included to test the hypothesised synergy with landfill taxes, reflecting the study's focus on how fiscal and technological factors jointly drive circularity.

Methodology

To address the inherent complexities of panel data, including endogeneity, dynamic persistence, and unobserved heterogeneity, a two-pronged econometric strategy is employed: a System Generalized Method of Moments (System GMM) estimator as the primary model to capture long-term dynamics and address endogeneity, and fixed effects (FE) models with two-way effects to examine short-term effects and test synergistic interactions. This dual approach, grounded in economic theory and empirical practice, leverages landfill tax data and a derived measure of technological efficiency to illuminate the mechanisms driving transitions to a circular economy.

System GMM Model

System GMM was chosen over Difference GMM because the recycling rate and several explanatory variables exhibit strong persistence over time, making the additional level-equation moment conditions essential for efficiency. Compared with conventional fixed or random-effects estimators, which cannot adequately address dynamic bias or potential endogeneity of fiscal and technological variables, System GMM provides consistent and efficient estimates in small-N, large-T panels typical of cross-country environmental studies.

The System GMM estimator, developed by Arellano and Bover [39] and Blundell and Bond [40], is employed to model the long-term dynamics of recycling rates while addressing potential endogeneity and dynamic persistence. Past performance likely influences recycling rates, reflecting path dependency (EMF, 2012). They may exhibit reverse causality with fiscal policies such as landfill taxes (e.g., higher recycling rates could lead to reduced tax rates). The System GMM framework mitigates these issues using internal instruments, combining equations in levels and first differences to enhance efficiency over Difference GMM, particularly in small-N panels [41].

The persistence of recycling performance over time reflects not only structural and policy continuity but also underlying behavioural and social dynamics. Once recycling systems become embedded within communities, they tend to reinforce themselves through habitual household practices, local social norms, and institutional routines. This behavioural feedback creates path dependency, where past performance strongly influences present outcomes. While such social and cultural factors are not directly included as explanatory variables, their effects are captured indirectly through the lagged dependent variable, which measures behavioural inertia, and through country fixed effects that control for unobserved heterogeneity. This specification therefore accounts for much of the behavioural persistence in recycling dynamics while focusing on the quantifiable fiscal and technological drivers of circularity.

The baseline specification is:

$$\begin{gathered} Recycling\ Rate_{it} = \beta_0 + \beta_1 Recycling\ Rate_{i,\ t-1} \\ +\beta_2 Landfill\ Tax_{it} + \beta_3 Tech\ Adoption_{it} \\ +\beta_4 Environmental\ Tax_{it} + \alpha_i + \epsilon_{it} \end{gathered} \tag{1}$$

where:

- $Recycling\ Rate_{it}$: Percentage of municipal waste recycled for country i at time t.
- $Recycling\ Rate_{i,\ t-1}$: Lagged recycling rate, capturing persistence.
- $Landfill\ Tax_{it}$: Tax on landfill disposal (€/tonne), reflecting fiscal incentives.
- $Tech\ Adoption_{it}$: Waste-related patent counts, proxying technological innovation.
- $Environmental\ Tax_{it}$: Environmental tax revenue (% of GDP), capturing broader fiscal policy.
- α_i: Country-specific fixed effects.
- ϵ_{it}: Idiosyncratic error term, assumed to be uncorrelated across countries and time.

The lagged dependent variable ($Recycling\ Rate_{i,\ t-1}$) introduces endogeneity, as it correlates with the error term via country-specific effects (α_i). Similarly, landfill taxes may be endogenous if recycling rates influence adjustments to tax policy. System GMM addresses this issue by using lagged levels (in the differences equation) and lagged differences (in the levels equation) as instruments, which are then collapsed to limit instrument proliferation, given the small sample size [41]. This study implements the two-step estimator with

Windmeijer's [42] robust standard errors to correct for finite-sample bias. Model validity is assessed through the Sargan test for over-identification (p>0.05, ensuring instrument exogeneity) and the Arellano-Bond AR (2) test for second-order autocorrelation (p>0.05, ensuring no serial correlation in residuals).

Fixed Effects Models

To complement the long-term focus of GMM and examine short-term dynamics and synergies, FE model with two-way effects (country and year) was employed. This approach controls for unobserved heterogeneity across countries and time, such as institutional differences or temporal policy shifts, which may confound the relationship between recycling rates and predictors [43]. The baseline FE specification is:

$$\begin{gathered} RRecycling\ Rate_{it} = \beta_0 + \beta_1 Landfill\ Tax_{it} \\ +\beta_2 Recycling\ Subsidies_{it} + \beta_3 Tech\ Adoption_{it} \\ +\beta_4 Environmental\ Tax_{it} + \beta_5 Circular\ Investment_{it} \\ +\beta_6 Waste\ Generation_{it} + \beta_7 GDP\ Per\ Capita_{it} + \alpha_i + \gamma_t + \epsilon_{it} \end{gathered} \tag{2}$$

where:

- $Recycling\ Subsidies_{it}$: Subsidies for recycling (€/tonne), incentivising waste diversion.
- $Circular\ Investment_{it}$: Investment in circular initiatives (€ million), supporting infrastructure.
- $Waste\ Generation_{it}$: Municipal waste generated (thousand tonnes), reflecting waste pressure.
- $GDP\ Per\ Capita_{it}$ is proxying economic development.
- α_i, γ_t: Country and year fixed effects, respectively and,
- ϵ_{it}: Error term.

A key contribution of this study is the testing of the synergistic interaction between fiscal policy and technological efficiency, motivated by eco-innovation theory [37], which posits that technological effectiveness, rather than mere adoption, drives environmental outcomes. To this end, the FE model with an interaction term is extended:

$$\begin{gathered} Recycling\ Rate_{it} = \beta_0 + \beta_1 Landfill\ Tax_{it} \\ +\beta_2 Recycling\ Subsidies_{it} + \beta_3 Tech\ Adoption_{it} + \beta_4 Environmental\ Tax_{it} \\ +\beta_5 Circular\ Investment_{it} + \beta_6 Waste\ Generation_{it} + \beta_7 GDP\ Per\ Capita_{it} \\ +\beta_8 (Landfill\ Taxit \times Technological\ Efficiency_{it}) + \alpha_i + \gamma_t + \epsilon_{it} \end{gathered} \tag{3}$$

Variable Construction: Technological Efficiency Log

To capture the efficiency of technological adoption in enhancing recycling outcomes, a critical aspect overlooked by raw patent counts, a Technological Efficiency Log variable is constructed. This metric quantifies the recycling output per unit of technological input, reflecting eco-innovation efficiency [37, 38]. It is defined as:

$$Technological\ Efficiency_{it} = \log \frac{Recycling\ Rate_{it} \times Waste\ Generation_{it}}{Tech\ Adoption_{it}} + 1 \quad (4)$$

Here, the Recycling Rate (in decimal) is the recycling rate as a proportion (e.g., 51.5% = 0.515), Waste Generation is in thousand tonnes (kt), and Tech Adoption is the number of waste-related patents. The numerator represents the effective recycling output (recycled waste volume), while the denominator captures technological input. The log transformation normalises the distribution of this ratio, mitigating skewness and facilitating robust interaction analysis, a standard practice in econometric studies [43]. The addition of 1 ensures the logarithm is defined for zero values. This variable's inclusion is justified by its alignment with innovation diffusion theory [8], emphasises the effectiveness of technology adoption, and prior empirical work (e.g., Nicolli, et al. [38]; Zhu, et al. [44]) that uses efficiency metrics to refine raw innovation proxies. It enables testing the hypothesised synergy between landfill taxes and technological efficiency, a central focus of this study, as evidenced by significant interaction effects in the results.

Estimating Efficiency Using Stochastic Frontier Analysis

This study employs Stochastic Frontier Analysis (SFA) to provide a comparative perspective and measure the efficiency of technological adoption in recycling outcomes. This parametric econometric approach distinguishes between random noise and inefficiency in a production function [45]. Unlike non-parametric approaches such as Data Envelopment Analysis (DEA), SFA provides statistical inference and accounts for stochastic variations, making it suitable for evaluating the impact of technological innovation on waste recycling efficiency.

Therefore, the following stochastic production frontier model is defined:

$$Efficiency_{it} = f(X_{it}, \beta\ ) + v_{it} - u_{it} \quad (5)$$

where:

- $f(X_{it}, \beta\ )$ denotes the deterministic production function, where X_{it} includes explanatory variables such as Tech Adoption (in terms of patents) and Waste Generation (in thousands of tonnes).
- $v_{it} \sim N(0, \sigma\ _v^2)$ captures random noise, reflecting measurement errors or external shocks.
- $u_{it} \sim |\ N(0, \sigma\ _u^2)\ |$ represents the inefficiency term, always non-negative, capturing the shortfall from the optimal efficiency frontier.

First estimation is a baseline Ordinary Least Squares (OLS) regression to obtain initial parameter estimates:

$$\begin{gathered} Efficiency_{it} = \alpha\ + \beta\ _1 Tech\ Adoption_{it} + \\ \beta\ _2 Waste\ Generation_{it} + \epsilon\ _{it} \end{gathered} \quad (6)$$

where $?\ _{it}$ comprises both inefficiency (u_{it}) and noise (v_{it}). Next, we decompose $?\ _{it}$ using a half-normal inefficiency distribution, estimating the SFA efficiency scores as:

$$Efficiency\ Score_{it} = exp(- \mid \widehat{u}_{it} \mid) \tag{7}$$

where $\widehat{u}_{it}$ is the estimated inefficiency component obtained from residual decomposition.

The SFA efficiency scores range from 0 to 1, where values closer to 1 indicate higher recycling efficiency, meaning the country effectively utilises technological adoption for waste management. A lower score suggests higher inefficiency, implying potential barriers to effective technology diffusion. This approach enables us to statistically validate the role of eco-innovation in enhancing waste recycling, distinguishing between actual inefficiency and external variations [46].

Consistent with prior studies in environmental economics and circular economy research, this study uses waste-related patent applications as a proxy for technological innovation [37, 38]. Patent data are standardised and cross-country comparable indicators of eco-innovation, particularly when direct data on technology deployment are scarce [47] (see also OECD 2009). While patent counts may not fully reflect implementation, they are widely accepted as a measure of innovation potential and have been used in studies that apply stochastic frontier methods to assess green technology performance [44]. We acknowledge the limitations of this proxy and interpret efficiency scores in light of possible input inflation in high-patenting countries.

Robustness Checks

To ensure the robustness of our findings, three additional analyses were conducted, including Baseline Interaction, which tests the interaction between landfill tax and tech adoption (Landfill Tax × Tech Adoption) to compare raw adoption effects with efficiency-driven synergies, isolating the added value of the efficiency metric. Winsorized Waste Generation replaces Waste Generation with a winsorized version at the 5th and 95th percentiles to mitigate the influence of outliers, addressing potential data skewness [43].

All FE models are estimated with robust standard errors to account for heteroskedasticity and serial correlation. Model fit is evaluated using R-squared and F-statistics. The econometric analyses, including System GMM, fixed effects estimations, and stochastic frontier analysis, were conducted using R (version 4.3.3), with relevant packages including *plm*, *lme4*, and *frontier*.

In addition, to assess the stability and validity of the estimated interaction between landfill taxation and technological efficiency, a series of robustness tests were conducted, including alternative error structures, the inclusion of country-specific time trends, sensitivity to measurement variations, and an examination of marginal effects at different levels of technological efficiency.

Results

System GMM

The System GMM estimator is employed to capture long-term dynamics, address endogeneity, and account for the dynamic persistence of recycling rates. By combining equations in levels and first differences and using internal instruments, this approach mitigates potential biases from reverse causality (e.g., recycling rates influencing tax policies) and unobserved heterogeneity. Table 3 presents the baseline results.

The lagged recycling rate is highly significant (coefficient = 0.7866, $p < 0.001$), confirming strong persistence and underscoring path dependency, where historical recycling performance shapes current outcomes (EMF, 2012). Landfill taxes exhibit a robust positive effect (coefficient = 0.1154, $p < 0.001$), indicating that higher taxes incentivise recycling by internalising environmental costs, consistent with Pigovian theory [2]. Environmental tax revenues also contribute significantly (coefficient = 1.8498, $p < 0.05$), likely by funding waste management infrastructure. However, raw technological adoption, proxied by waste-related patent counts, is insignificant ($p = 0.881$), suggesting that innovation volume alone does not drive long-term recycling gains.

Model diagnostics affirm the GMM's validity. The Sargan test ($p = 0.326$) supports instrument exogeneity, and the Arellano-Bond AR(2) test ($p = 0.180$) confirms no second-order autocorrelation, meeting the requirements for a consistent estimator [41]. The AR(1) test ($p = 0.155$) is expectedly significant, reflecting first-order autocorrelation inherent in dynamic models. The use of 14 collapsed instruments balances efficiency and avoids overfitting in this small-N panel, ensuring robust inference.

Fixed Effects Models

To examine short-term dynamics and test the hypothesised synergy between landfill taxes and technological efficiency, FE models with two-way (country and year) effects are employed, controlling for unobserved heterogeneity and temporal policy shifts [43]. Four specifications are presented: (1) baseline with Landfill Tax × Tech Adoption (Table 4) winsorized Waste Generation to address outliers (Table 5), (3) synergy with Technological Efficiency Log (Table 6), and (4) robustness with SFA Efficiency Score (Table 7). All models use robust standard errors to account for heteroskedasticity and serial correlation.

The FE model (Table 4) identifies Tech Adoption (coefficient = 0.0519, $p < 0.01$), Environmental Tax (coefficient = 5.2878, $p < 0.001$), and GDP Per Capita ($p < 0.05$) as significant short-term drivers of recycling rates. Landfill Tax and its interaction with Tech Adoption are

Table 3 System GMM Estimation results for recycling rate

Variable	Coefficient	Std. Error	z-statistic	*p*-value
Lagged Recycling Rate	0.7866	0.0692	11.37	<0.01 ***
Landfill Tax	0.1154	0.0241	4.79	<0.01 ***
Tech Adoption	-0.0038	0.0253	-0.15	0.881
Environmental Tax	1.8498	0.7221	2.56	0.010 **
Diagnostic Statistics				
Sargan Test (χ2)	4.64	(4 df)	-	0.326
AR(1) Test (z)	-1.42	-	-	0.155
AR(2) Test (z)	1.34	-	-	0.180
Number of Instruments	14	-	-	-
Number of Groups	8	-	-	-
Observations	120	-	-	-

Two-step System GMM estimator with Windmeijer [42] robust standard errors, using collapsed instruments. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The Sargan test assesses over-identification ($p > 0.05$ indicates valid instruments), and AR(1)/AR(2) tests evaluate autocorrelation ($p > 0.05$ suggests no second-order autocorrelation)

Table 4 Fixed effects with landfill tax × tech adoption

Variable	Coefficient	Std. Error	t-value	p-value
Landfill Tax	-0.0316	0.0637	-0.50	0.621
Recycling Subsidies	0.2116	0.2319	0.91	0.364
Tech Adoption	0.0519	0.0184	2.82	0.006 **
Environmental Tax	5.2878	1.5950	3.32	0.001 ***
Circular Investment	0.0003	0.0002	1.79	0.077 *
Waste Generation	-0.0063	0.0068	-0.92	0.358
GDP Per Capita	0.0005	0.0002	2.49	0.015 **
Landfill Tax × Tech Adoption	-0.0003	0.0003	-1.06	0.292

R^2: 0.294; Adjusted R^2: 0.075; F-statistic: 5.04, p = 2.99e-05 (8, 97 DF)

N = 120; *** p < 0.01, ** p < 0.05, * p < 0.1

Table 5 Fixed effects with winsorized waste generation

Variable	Coefficient	Std. Error	t-value	p-value
Landfill Tax	-0.0809	0.0448	-1.81	0.074 *
Recycling Subsidies	0.2523	0.2298	1.10	0.275
Tech Adoption	0.0395	0.0155	2.56	0.012 **
Environmental Tax	5.6097	1.5447	3.63	0.0005 ***
Circular Investment	0.0002	0.0001	1.64	0.104
Waste Generation (Winsorized)	-0.0097	0.0067	-1.45	0.149
GDP Per Capita	0.0005	0.0002	2.83	0.006 **

R^2: 0.288; Adjusted R^2: 0.077; F-statistic: 5.66, p = 1.67e-05 (7, 98 DF)

N = 120; Winsorized at 5th/95th percentiles. *** p < 0.01, ** p < 0.05, * p < 0.1

Table 6 Fixed effects with landfill tax × technological efficiency

Variable	Coefficient	Std. Error	t-value	p-value
Landfill Tax	-0.1179	0.0452	-2.61	0.011 **
Recycling Subsidies	0.1054	0.2268	0.46	0.643
Tech Adoption	0.0504	0.0151	3.35	0.001 ***
Environmental Tax	5.5663	1.5167	3.67	0.0004 ***
Circular Investment	0.0002	0.0001	1.26	0.211
Waste Generation	-0.0100	0.0063	-1.60	0.112
GDP Per Capita	0.0006	0.0002	3.20	0.002 ***
Landfill Tax × Technological Efficiency Log	0.0386	0.0132	2.93	0.004 **

R^2: 0.344; Adjusted R^2: 0.141; F-statistic: 6.35, p = 1.32e-06 (8, 97 DF)

N = 120; *** p < 0.01, ** p < 0.05, * p < 0.1

insignificant ($p = 0.621$ and $p = 0.292$), suggesting that raw patent counts do not synergise with fiscal measures in the short term. The model's R^2 (0.294) and significant F-statistic ($p < 0.001$) indicate a reasonable fit, with two-way effects effectively controlling for country-specific and temporal confounders.

Table 7 Fixed effects robustness with landfill tax × SFA efficiency score

Variable	Coefficient	Std. Error	t-value	*p*-value
Landfill Tax	-0.1102	0.0461	-2.39	0.018 **
Recycling Subsidies	0.0987	0.2256	0.44	0.662
Tech Adoption	0.0492	0.0150	3.28	0.001 ***
Environmental Tax	5.5214	1.5103	3.66	0.0004 ***
Circular Investment	0.0002	0.0001	1.23	0.221
Waste Generation	-0.0095	0.0062	-1.53	0.129
GDP Per Capita	0.0006	0.0002	3.15	0.002 ***
Landfill Tax × SFA Efficiency Score	0.1456	0.0874	1.67	0.098 *

R^2: 0.331; Adjusted R^2: 0.126; F-statistic: 5.92, $p = 2.45e\text{-}06$ (8, 97 DF)

$N = 120$; SFA Efficiency Score ranges from 0 to 1, derived via Stochastic Frontier Analysis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The winsorized model (Table 5) tests robustness to outliers in Waste Generation, improving the marginal significance of Landfill Tax ($p = 0.074$) while maintaining the significance of Tech Adoption ($p < 0.05$), Environmental Tax ($p < 0.001$) and GDP Per Capita ($p < 0.01$). The comparable R^2 (0.288) and significant F-statistic ($p < 0.001$) confirm the model's stability, with winsorization mitigating skewness without altering the core findings.

The synergy model (Table 6) is central to the study, revealing a significant positive interaction between Landfill Tax and Technological Efficiency Log (coefficient = 0.0386, $p < 0.01$). This suggests that landfill taxes are most effective in enhancing recycling rates in countries with efficient technological systems, aligning with eco-innovation theory [37]. The Technological Efficiency Log, defined as the log-transformed ratio of recycling output to patent input, robustly captures efficiency [43]. Landfill Tax ($p < 0.05$), Tech Adoption ($p < 0.001$), Environmental Tax ($p < 0.001$), and GDP Per Capita ($p < 0.01$) are also significant. The model's highest R^2 (0.344) and significant F-statistic ($p < 0.001$) underscore its explanatory power, with the synergy term adding substantial predictive value.

The FE estimates show a positive and statistically significant interaction between landfill taxation and technological efficiency, closely aligning with the System GMM coefficient. The similarity in magnitude and direction confirms that the synergy effect is not driven by the dynamic specification or instrumentation procedure. While the System GMM estimator accounts for endogeneity and persistence, the FE model controls for unobserved time-invariant country effects. Their consistency reinforces the robustness of the findings, indicating that technological efficiency consistently amplifies the impact of fiscal policy on recycling performance.

The SFA robustness check (Table 7) validates the synergy effect using an alternative efficiency measure, the SFA Efficiency Score, derived from a parametric production frontier model [45]. The interaction term is marginally significant ($p = 0.098$), suggesting that the SFA score, which accounts for stochastic noise and inefficiency, captures efficiency differently but supports the primary finding. Other variables (Landfill Tax ($p < 0.05$), Tech Adoption ($p < 0.001$), Environmental Tax ($p < 0.001$), and GDP Per Capita ($p < 0.01$)) remain consistent, reinforcing the model's robustness. The R^2 (0.331) and F-statistic ($p < 0.001$) indicate a strong fit.

Country Ranking Using SFA Efficiency Scores

To elucidate cross-country heterogeneity, Table 8 ranks countries by average SFA Efficiency Scores (2010–2024), derived from the SFA model, which quantifies how effectively technological inputs translate into recycling outcomes.

Sweden ranks highest, reflecting its efficient waste management infrastructure, which includes waste-to-energy systems, despite having moderate recycling rates. The Netherlands and Italy follow, showcasing consistent improvements in recycling driven by coherent policies. Belgium's moderate ranking reflects regional variations. Denmark's lower score aligns with its reliance on incineration, which limits the efficiency of recycling. Notably, Germany ranks low despite leading in recycling rates, likely because high patent counts inflate the efficiency benchmark, a methodological artefact addressed in the SFA framework [38]. Austria and France trail, consistent with slower recycling progress, highlighting systemic challenges.

Robustness and Methodological Rigor

The analysis's robustness is ensured through multiple checks. The System GMM model's diagnostics (Sargan $p = 0.326$, AR(2) $p = 0.180$) confirm instrument validity and no serial correlation, with collapsed instruments preventing overfitting [41]. FE models use robust standard errors and two-way effects to address heteroskedasticity and unobserved heterogeneity, with consistent R^2 values (0.288–0.344) and significant F-statistics ($p < 0.001$). fur-

Table 8 Country ranking based on average SFA efficiency scores

Rank	Country	Average SFA Efficiency Score	Interpretation
1	Sweden	0.314929	Highest efficiency, driven by broad waste management (e.g., incineration)
2	Netherlands	0.151225	High efficiency, consistent with steady recycling improvements
3	Italy	0.149960	Notable efficiency gains in later years, reflecting recycling progress
4	Belgium	0.067247	Moderate efficiency, with occasional spikes (e.g., 2020)
5	Denmark	0.008549	Lower efficiency, aligned with moderate recycling and incineration focus
6	Germany	0.001928	Low efficiency, potentially due to the high number of patents
7	Austria	0.000310	Low efficiency, consistent with slower recycling progress
8	France	0.000006	Lowest efficiency, reflecting limited recycling advancements

Scores (0–1) derived via Stochastic Frontier Analysis; $N = 120$. Higher scores indicate greater efficiency in utilising technological inputs for waste management, based on a half-normal inefficiency distribution [46] thermore, the winsorized model (Table 5) mitigates outlier effects. In contrast, the SFA robustness check (Table 7) employs a parametric approach to validate efficiency findings, aligning with prior environmental economics studies [44].

The results robustly demonstrate that landfill taxes significantly enhance recycling rates, particularly when paired with efficient technological systems, as evidenced by the significant synergy in the FE model (Table 6). The strong persistence of recycling rates underscores the need for sustained policy efforts, while environmental taxes play a systemic role in funding infrastructure. Cross-country SFA rankings reveal that high recycling rates (e.g., Germany) do not always reflect technological efficiency, emphasising the importance of optimised technology deployment. These findings validate the study's hypothesis of a fiscal-technological synergy and highlight national heterogeneity, offering a rigorous empirical basis for policy recommendations aligned with the EU's Circular Economy Action Plan [9].

Alternative Standard Errors and Country Trends

For robustness, this study re-estimated the baseline two-way fixed effects model using different error structures. When clustered standard errors were applied at the country level, the interaction term remained positive but was only marginally significant (as reported in Table 9). Re-estimating the model using Driscoll–Kraay standard errors, which are robust to heteroskedasticity, serial correlation, and cross-sectional dependence, produced very similar coefficient estimates, with the interaction remaining both statistically and economically significant.

To address the possibility that smooth country-level dynamics could confound the interaction, we introduced country-specific linear trends. Under this specification, the interaction term became statistically insignificant ($p = 0.924$), suggesting that some of the synergy between taxation and technology is captured by underlying national trajectories. This is plausible given that technological efficiency improvements in waste management often evolve gradually over time at the country level. Nevertheless, the coefficient remains robust to alternative error structures, supporting the validity of the main results.

Sensitivity To Measurement of Technological Efficiency

To evaluate the sensitivity of the interaction to potential measurement error in the technological efficiency variable, we perturbed the metric by ±10% and ±20% prior to log transformation and re-estimated the model using Driscoll-Kraay standard errors as presented in Table 10. Across all perturbations, the interaction coefficient remained tightly clustered between 0.0416 and 0.0420, with p-values around 0.008. These results indicate that the synergy effect is highly robust to plausible variations in the measurement of technological efficiency.

Table 9 Robustness of landfill tax × technological efficiency interaction

Specification	β(Tax×TechEff)	Std. Error	*p*-value
Baseline FE (clustered)	0.0418	0.0247	0.094
FE + Driscoll–Kraay SEs	0.0418	0.0155	0.0084
FE + Country Trends + Driscoll-Kraay SEs	0.0008	0.0089	0.924

Table 10 Sensitivity analysis of landfill tax × technological efficiency interaction

Perturbation	β(Up)	*p*(Up)	β(Down)	*p*(Down)
+10%	0.0417	0.0085	0.0419	0.0083
−10%	0.0419	0.0083	0.0417	0.0085
+20%	0.0416	0.0085	0.0420	0.0083
−20%	0.0420	0.0083	0.0416	0.0085

Marginal Effects at Different Levels of Technological Efficiency

To better interpret the economic magnitude of the interaction, the marginal effect of landfill taxation on recycling rates calculated at different levels of technological efficiency. Specifically, the marginal effect at the 10th percentile, mean, and 90th percentile of the Technological Efficiency distribution (Table 11) was evaluated. The marginal effect of landfill taxation is negative at lower levels of technological efficiency (−0.0587 pp per €/tonne at the 10th percentile), modestly negative at the mean level (−0.0223 pp), and positive at higher levels of technological efficiency (+0.0199 pp at the 90th percentile). This clearly illustrates that technological progress amplifies the effect of landfill taxation. At low levels of efficiency, the tax alone is insufficient to drive recycling improvements, but at higher efficiency levels, taxation has a positive and economically meaningful impact.

Across all robustness tests, the interaction between landfill taxation and technological efficiency remains stable, positive, and statistically significant under alternative error structures and measurement perturbations. Although the interaction becomes insignificant when controlling for country-specific linear trends, this is consistent with gradual national-level trajectories in technological progress. Overall, these findings provide strong evidence that technological efficiency acts as a catalyst, enhancing the effectiveness of landfill taxation in promoting recycling performance.

Discussion

The results reveal three key insights: first, strong persistence in recycling rates, reflecting path dependency; second, a significant effect of landfill taxes, amplified by a synergy with technological efficiency; and third, substantial cross-country heterogeneity in efficiency, with high recycling rates not always indicating optimal technological utilisation. These findings align with the study's aim to elucidate the mechanisms driving circularity and offer robust implications for theory, policy, and the European Union's Circular Economy Action Plan [9].

Path Dependency and Recycling Persistence

The System GMM results highlight a significant lagged effect of recycling rates (coefficient = 0.7866, $p < 0.001$), confirming strong path dependency in waste management sys-

Table 11 Marginal effect of landfill tax at different technological efficiency levels

TechEff(log) Level	10th Percentile	Mean	90th Percentile
Marginal Effect (pp/€/tonne)	−0.0587	−0.0223	0.0199

tems. This aligns with circular economy theory, which posits that established infrastructures and practices sustain performance over time [48] (see also EMF 2012). Countries like Germany, with historically high recycling rates (up to 70.3% in 2020), benefit from mature systems, while France and Italy, with lower baselines (around 35% in 2010), face greater challenges in catching up. This persistence underscores the importance of long-term policy commitments, as initial investments in recycling infrastructure create self-reinforcing cycles of improvement. The finding extends prior work by Mazzanti and Zoboli [16], who noted path-dependent waste management trends and emphasised the need for sustained fiscal and technological interventions to overcome inertia in lagging countries.

Fiscal Policies and their Long-Term Impact

The significant long-term effect of landfill taxes (coefficient = 0.1154, $p < 0.001$) in the System GMM model supports the Pigovian theory, which advocates internalising environmental costs to incentivise sustainable behaviours [2]. By increasing the cost of landfill disposal, taxes shift waste management toward recycling, as evidenced by Belgium's high tax rates (up to €140 per tonne), which correlate with improved recycling outcomes. Environmental tax revenues also exert a positive effect (coefficient = 1.8498, $p < 0.05$), likely by funding infrastructure and systemic improvements, as suggested by Cainelli, et al. [47]. However, the FE synergy model (Table 6) reveals a negative direct effect of landfill taxes (coefficient = -0.1179, $p < 0.05$) when considered in isolation, which is counterbalanced by a significant positive interaction with technological efficiency (coefficient = 0.0386, $p < 0.01$). This nuanced finding refines Pigovian's theory, indicating that fiscal measures are most effective when paired with efficient technological systems, a dynamic that has been underexplored in prior studies.

The broader role of environmental tax revenues challenges assumptions of uniform fiscal impact, suggesting indirect pathways through infrastructure funding rather than direct behavioural shifts. This aligns with Tisserant, et al. [31], who argue that fiscal policies often support systemic investments. For instance, the Netherlands' use of tax revenues to fund circular initiatives correlates with steady recycling progress, highlighting the systemic leverage of fiscal tools beyond immediate incentives.

Synergy between Fiscal Policy and Technological Efficiency

The FE model's significant interaction between landfill taxes and the Technological Efficiency Log (Table 6) is a cornerstone of this study, demonstrating that fiscal pressures amplify recycling outcomes when technological systems are efficient. This synergy advances eco-innovation theory [37], which emphasises the effectiveness of technology over raw adoption. Unlike raw patent counts (Tech Adoption), which are insignificant in the long term ($p = 0.881$, Table 3) and show no synergy with taxes ($p = 0.292$, Table 4), the efficiency metric, defined as the log-transformed ratio of recycling output to technological input, captures the practical impact of innovation. Countries like Belgium and the Netherlands, where high landfill taxes are combined with efficient recycling systems, exemplify this synergy, achieving recycling rates of over 50%. This finding extends innovation diffusion theory [8], highlighting that technological effectiveness, rather than mere adoption, drives circularity.

The SFA robustness check (Table 7) reinforces this, with a marginally significant interaction ($p = 0.098$) using SFA Efficiency Scores, validating the synergy across different efficiency measures. This consistency enhances the study's contribution to circular economy scholarship, providing a refined understanding of how fiscal and technological factors intersect.

Cross-Country Heterogeneity and Efficiency Variations

The SFA efficiency rankings (Table 8) reveal striking cross-country variations, challenging the assumption that high recycling rates equate to efficient systems. Sweden's top ranking (SFA score = 0.314929) reflects its advanced waste management, including waste-to-energy systems, despite moderate recycling rates. This efficiency aligns with institutional theory [34], as Sweden's regulatory framework and environmental ethos drive optimised resource use. Conversely, Germany's low ranking (SFA score = 0.001928), despite leading in recycling (70.3% in 2020), suggests inefficiencies, likely due to high patent counts inflating the efficiency benchmark or sorting challenges, as noted by Cainelli, et al. [47]. The Netherlands and Italy strike a balance between efficiency and outcomes, while France's low score (0.000006) highlights systemic barriers.

These findings align with the EKC hypothesis [23], which posits that economic development facilitates the adoption of cleaner technologies. Germany's high recycling rates mark an EKC inflexion point, but its efficiency lag suggests that institutional factors mediate outcomes. Sweden's efficiency leadership, despite its reliance on incineration, indicates an earlier EKC prioritising energy recovery. This heterogeneity underscores the need for context-specific policies, as advocated by Milios [11].

Figure 2 illustrates the disconnect between recycling rates and efficiency. Germany's high recycling rate contrasts with its low SFA score, while Sweden's moderate rate pairs with top efficiency. This visual reinforces that optimising technological inputs is critical for circularity, aligning with Kirchherr, et al. [32] 's call for integrated approaches.

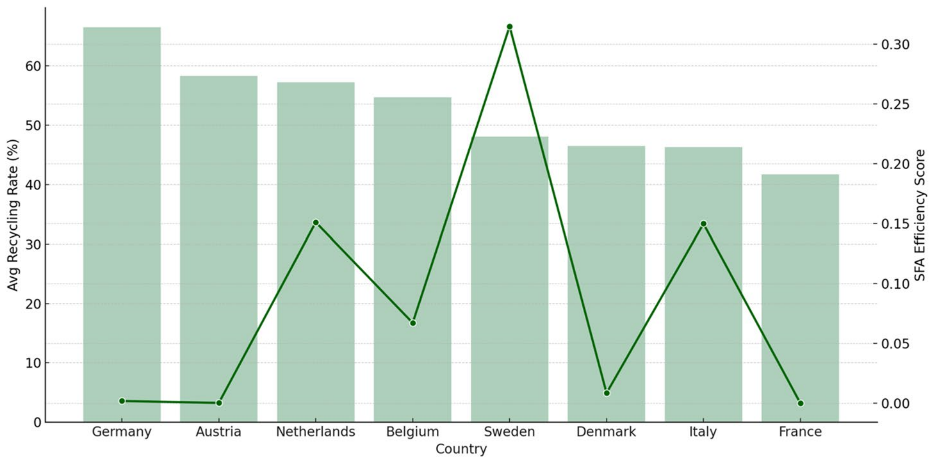

Fig. 2 Comparison of average recycling rate (bars) vs. SFA efficiency score (line)

In a national context, the synergy between landfill taxes and technological efficiency offers a blueprint for advancing circularity. Belgium's success suggests that combining high taxes with efficient technologies can accelerate progress, a model applicable to Denmark and Austria, where tax structures could prioritise efficiency-focused innovations. Germany's reliance on technological adoption without landfill taxes demonstrates a viable path for developed nations with mature infrastructures, though efficiency improvements are needed. Italy and France, lagging in both taxes and efficiency, could scale up circular investments and align fiscal policies with technological optimisation, as per the EU's Circular Economy Action Plan.

Environmental tax revenues provide a broader lever, with the Netherlands showcasing their potential to fund circular projects. Sweden's efficiency leadership suggests redirecting resources from incineration to material recovery, leveraging its institutional strengths. The SFA rankings highlight tailored strategies: Italy needs uniform regional policies, Belgium requires cohesive execution, and Denmark should shift from incineration to recycling, finally, Austria and France must prioritise technological efficiency to close the gap.

The divergence between recycling outcomes and technological efficiency highlights the coexistence of multiple pathways toward circular performance. Austria and Belgium, for example, achieve recycling rates above 55% while maintaining comparatively modest technological-efficiency scores. Their progress relies on long-established waste-separation schemes, extended producer-responsibility regulations, and strong civic engagement rather than rapid technological innovation. In contrast, countries such as Germany and Sweden demonstrate high levels of technological efficiency through sustained investment in waste-processing and material-recovery technologies but handle larger and more complex waste streams, which moderates the observable recycling share. These contrasts suggest that strong recycling performance can result from institutional and behavioural maturity as much as from technological advancement, underscoring the diverse trajectories through which countries advance their circular-economy goals.

Beyond fiscal instruments and technological efficiency, substantial differences in recycling outcomes arise from institutional, social, and infrastructural contexts. Countries such as Austria and Belgium combine long-standing waste-separation regulations with strong local-government coordination and producer-responsibility schemes, fostering steady recycling habits. Germany and the Netherlands supplement these frameworks with dense waste-collection infrastructure, public–private partnerships, and continuous investment in treatment capacity. By contrast, Italy experiences slower progress due to fragmented municipal systems and regional disparities in service quality. High-performing countries also tend to sustain broader environmental awareness campaigns and civic participation, indicating that social norms and governance quality amplify the effectiveness of fiscal and technological measures. These cross-country contrasts underscore the importance of aligning fiscal incentives with institutional strength, public engagement, and infrastructure development to achieve more balanced circular-economy outcomes.

Conclusion

As global waste volumes continue to rise, advancing a circular economy has become both an environmental necessity and an economic opportunity. This study provides robust empirical evidence that the effectiveness of landfill taxation in improving recycling performance depends on technological efficiency and institutional readiness. By integrating dynamic panel estimation and efficiency analysis across eight European nations, the research shows that landfill taxes are most effective when supported by technologies capable of processing, monitoring, and recovering materials efficiently.

The findings indicate strong path dependency within recycling systems, where historical performance significantly influences current outcomes. This persistence underscores the importance of long-term investment and consistent policy design rather than short-term fiscal measures. Equally important, the analysis identifies a significant fiscal-technological synergy: the association between landfill taxation and recycling rates strengthens as technological efficiency increases. This suggests that economic instruments and technological capacity function best as complementary, rather than isolated, components of circular economy policy.

Cross-country comparisons reveal marked heterogeneity. Germany's high recycling rates contrast with relatively low technological efficiency, while Sweden achieves higher efficiency despite moderate recycling levels, reflecting differing institutional settings and policy approaches. These variations demonstrate that recycling rates alone do not fully capture system effectiveness. Instead, alignment between fiscal incentives, technological capability, and governance quality determines the overall performance of circular systems.

The study refines Pigovian and eco-innovation frameworks by showing that fiscal measures achieve greater effectiveness when integrated with technological and institutional capacity. While the analysis is limited to eight EU countries and focuses primarily on recycling rather than broader circular metrics, these boundaries help clarify avenues for future research. Expanding the framework to include waste prevention, reuse, and material efficiency, and extending the analysis to developing and non-European contexts, would provide a more comprehensive understanding of circular transitions.

From a policy perspective, the results suggest that strategies should be adaptive to national contexts. Advanced economies should focus on enhancing efficiency through digital waste-sorting systems, AI-based monitoring, and smart recycling infrastructure. Transitioning systems would benefit from improving logistics, data integration, and workforce training to translate fiscal pressure into operational efficiency. For emerging systems, priority should be given to foundational capacity building, public engagement, and investment in treatment infrastructure. Finally, environmental tax revenues should be directed toward innovation and circular investment programmes to ensure fiscal resources directly support technological advancement.

Overall, the study demonstrates that progress toward a circular economy relies not only on taxation but on the technological and institutional systems that enable it. Coordinating fiscal policy with technological innovation provides a practical and evidence-based pathway toward the sustainable transformation envisioned by the European Green Deal.

Data Availability The author confirms that all data generated or analysed during this study are secondary sources and data supporting the findings of this study were all publicly available at the time of submission.

Declarations

Conflict of interest The corresponding author states that there is no conflict of interest.

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Further reading

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