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The impact of waste on resource and energy productivity: A circular economy perspective

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Abstract. As cities continue to grow, managing the increasing amount of waste has become an important concern. The study intends to assess the effects of waste generation and treatment on total resource productivity, as well as its subset, energy productivity, in European Union (EU) countries. The research employs the Driscoll-Kraay standard errors fixed effect model using panel regression. The findings reveal that waste generation impacts negatively on overall resource

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productivity and energy productivity. Furthermore, waste treatment also has a negative impact on resource productivity and energy productivity. These results suggest that despite the reduction in waste volumes achieved through treatment, the process may still have a negative relationship with productivity outcomes. The paper explores the underlying reasons for these findings and evaluates the status of waste generation and treatment across EU countries. Implications suggest introducing public-private partnerships to strengthen waste treatment processes, eco-tax solutions, incentives to green organizations, penalties for environmentally harmful practices, and improved data accessibility for informed decision-making. This study evaluates waste treatment techniques in the EU, focusing on the implementation of circular economy principles to promote sustainable development, increase resource productivity, and strengthen waste management frameworks.

Keywords: waste, circular economy, resources, energy, productivity
JEL Classification: Q01, Q2, Q5, Q20

1. INTRODUCTION

The world is currently experiencing severe consequences due to the escalation of waste generation. As cities are growing, the demand for goods and services is rising, contributing to more waste being produced daily. Climate change, environmental degradation, food insecurity, and health issues are major concerns that arise from waste generation (Dat & Hung, 2023; Plambeck & Taylor, 2013). Waste creates triple planetary concerns, which are climate change, biodiversity, and pollution. Circular economy practices advocate for waste prevention through the 3R strategy: reduce, reuse, and recycle to promote sustainability (Lopez et al., 2019); to keep resources in the economy for as long as feasible while reducing waste across multiple sectors (Stavropoulos & Burger, 2020). Waste generated by both businesses and homes, such as food waste, packaging, and electronic trash, can be effectively handled using these strategies, thereby lowering environmental impact and increasing resource productivity (Hossain et al., 2024). Materials, energy, water, capital, and labor are all examples of inputs that contribute to resource productivity (Anttonen, 2010). Resource productivity measures how the per unit of resources is used for economic growth (Vuta et al., 2018). Similarly, energy productivity (part of resource productivity) is per unit use of primary energy that contributes to economic growth (Steinberger & Krausmann, 2011). Economic growth typically leads to increased demand for raw materials, energy, and other natural resources. It also results in a higher volume of materials turning into waste if not managed effectively (Bringezu et al., 2004). When waste levels rise, it frequently indicates inefficiencies in material consumption, as more resources are consumed without contributing to final, usable products (Plambeck & Taylor, 2013). This inefficiency not only increases production costs but also necessitates greater resource consumption, thereby reducing productivity per unit of input. Additionally, managing and disposing of waste demands extra energy, time, and resources, diverting materials away from productive use. (Ball, 2015). Capital resources are less efficiently utilized as waste increases, often requiring additional investments in waste handling rather than productive assets (Macomber, 2013). Both developed and developing countries across the world use different measures to prevent waste and enhance resource productivity (Volk et al., 2019). For instance, in most nations, total waste generation (all sources of garbage) continues to rise in conjunction with population and economic expansion. Only a few nations, like Hungary, Japan, the Netherlands, and Spain, have successfully decoupled their total waste creation from economic growth. Turkey had the worst waste management system in 2022. Additionally, Turkey, Latvia, Chile, Mexico, and Italy are the countries with the most waste in 2022.

The European Union (EU) has made resource productivity one of the sustainable development indicators to attain sustainability. As per European Commission, in 2022, the EU generated 795 million tons of waste (excluding significant mineral waste), accounting for 36% of total waste generated. A large part of waste generation is from mining and quarrying, and the construction sector accounted for 64 percent in 2020. In 2022, the EU created an average of 1.8 tons of garbage per person, excluding major mineral waste that affects resource productivity. EU countries are included in most waste-producing countries as per the Global Waste Index (GWI), such as Latvia and Italy (European Commission, 2022). The European Union generates 850 million tons of building and demolition waste (CDW) annually. As per the European environmental board, the EU advises the implementation of non-binding measures and economic incentives to promote waste avoidance(European Environmental Board). These include landfill and incinerator levies, as well as initiatives to promote package reuse and ensure that consumers receive a small rebate when they return a container for recycling (Lee et al., 2024). Furthermore, the EU has long worked to achieve its policy objective of reducing waste by preventing waste formation, which is the first stage in the waste hierarchy outlined in the EU Waste Framework Directive (Baldassarre, 2025). The EU's zero-pollution objective is to considerably cut total waste by 2030. As per the European Environment Agency, the amounts created by EU Member States ranged from less than 1.5 tons per capita in Portugal to 21 tons per capita in Finland in 2020. Diverse levels reflect diverse economic structures, and extreme numbers and major variances can be influenced by country-specific circumstances (Vuta et al., 2018). 11 of the 27 EU Member States for 2020 exceeded the EU average waste production amount. In 2020, the average amount of waste generation per person was 4.8 tons, but these 11 EU countries show the worst numbers. For instance, Denmark and Luxembourg produced the most waste in 2020. Greece had the highest relative fall in the EU, while Latvia had the largest relative growth. These facts reveal that there is still a need to address the problem of waste generation and enhance waste management in the EU. These practices will help to increase resource productivity and will lead to sustainability and economic growth (Cainelli et al., 2020; Mishchuk et al., 2023).

By highlighting the importance of resource productivity, this study aims to examine the impact of waste overall on resource productivity and energy productivity separately (RO1). In addition to the first objective, the research delves into why waste has differing impacts on overall resource productivity and its integral component, energy productivity, despite their interconnected nature (RO2). Numerous reasons support these objectives, for instance, waste treatment can increase resource productivity by reusing materials, but it does not always increase energy productivity due to high energy expenditures in treatment operations (Plappally & others, 2012). Analyzing these consequences independently allows for a more sophisticated understanding of the trade-offs between material conservation and energy consumption in treatment, which adds depth to sustainable resource management approaches (Piwowarski, 2024; Kontautienė et al., 2024). Furthermore, Different impacts on resource and energy productivity may call for unique interventions. To fulfill these objectives, the study takes resource productivity and energy productivity as dependent variables. To show the importance of a circular economy, the research considers waste generation and waste treatment as independent variables. As economic growth and population also play key roles in determining the resource productivity in any economy, this study takes GDP (as an indicator of economic growth) and population as control variables. The study analyzes the 20-year data of 27 EU countries to examine the relationship between dependent and independent variables. To analyze the data, the study uses the Driscoll-Kraay standard errors fixed effect model, which overcomes the problem of heteroskedasticity, cross-sectional dependence, and serial correlation (Hoechle, 2007). Further, to determine the accuracy of data, the study uses the Levin-Lin-Chu test to check stationarity, the Westerlund test for cointegration, and the variance inflation factor to check multicollinearity. The results show that waste generation has a significant negative impact on resource productivity and energy productivity. Additionally, waste treatment also has a significant negative impact on resource productivity and energy productivity. For the robustness of results the study utilizes two-stage least squares (2SLS) method. These results indicate that waste treatment processes are not sufficient to increase resource productivity; the reason may be the insufficient process and high cost (Cingoski & Petrevska, 2018). The research provides various implications for policymakers and the government as well. These implications are: adopting a closed-loop system to prevent waste generation, binding targets for industries to follow waste prevention mechanisms, eco-label tax incentives for corporates, time-phased audits, advanced waste treatment technologies, public-private partnerships to reduce waste, and availability of data for decision-making. By inculcating these policy measures, waste treatment can be more effective in EU economies while enhancing resource productivity.

This study is divided into seven sections. The second section deals with the literature review, followed by the data and research methodology. The next section is the result section. The fifth section highlights the discussion of the results. The sixth section provides policy implications, followed by the conclusion.

2. LITERATURE REVIEW

Resource productivity is a critical indicator used to assess the efficiency of economic-environmental systems. It is typically defined as the economic output (usually measured in GDP) produced per unit of natural resources consumed (Aydin & Erdem, 2024). Furthermore, this measure reflects how efficiently various natural resources—such as raw materials, water, and energy—are utilized in economic activities (Liao et al., 2024). *Energy productivity*, a more specific component of resource productivity, measures the economic output generated per unit of energy input (GDP per unit of energy consumption) (Ul Hassan Shah et al., 2024). Numerous studies have analyzed the impact of these resources on economic growth, the environment, and sustainable development (Zhidebekkyzy et al., 2023; Toušek et al., 2025; Juracka & Valaskova, 2025). Kirikkaleli & Ali, (2024) include both asymmetric and symmetric autoregressive distributed lag (ARDL) techniques in the study. It implies that a positive shock in resource efficiency reduces pollution, but a negative shock in resource efficiency increases environmental pollution in Germany. Energy productivity impacts environmental pollution negatively. Finally, globalization raises consumption-related CO2 emissions. To boost resource productivity, we must prioritize developing and supporting water productivity, reducing energy dependence, utilizing renewable energy sources, and recycling (Svazas et al., 2023; Taušová et al., 2022). This study uses multiple regression of resource productivity and highlights that Europe is promoting a circular economy by implementing eco-innovations and utilizing waste as a secondary resource. The study analyses the impact of resource productivity on eco-innovation in two groups of EU members and V4 countries- Slovakia, the Czech Republic, Poland, and Hungary. The evaluation is based on eight basic indicators for resource efficiency and seven indicators from theme areas to consider potential implications. Model V4 implies insignificant mentions of the reason for insufficient circular economy implementations in these countries. It identifies water productivity, energy dependence, energy productivity, and environmental tax as the most significant factors. Petkovic et al., (2022) use a neuro-fuzzy inference system aimed at discovering which sector's energy or non-energy material productivity has a greater impact on the GDP of OECD members. The results entail that non-energy productivity has a larger impact on GDP and could be used as the best practice for the implementation of the circular economy concept. Kumar & Samadder (2017) observed a strong negative correlation between per capita waste generation and resource productivity in the EU, with higher waste generation linked to lower resource efficiency. This is particularly true for countries with less developed waste management systems or higher rates of landfilling. Recent studies have also highlighted the role of technological innovation in improving the efficiency of waste management systems. Alsabt et al. (2024) found that nations investing in advanced sorting and treatment technologies generally achieved better resource productivity outcomes, even though these technologies may increase energy consumption in the waste management sector. This suggests that technological innovation could be key to optimizing the trade-offs between resource and energy productivity. Similarly, Münch et al., (2022) depict that because it is difficult to recycle automobiles, the rapid speed of technological advancement is resulting in increased resource use and possibly higher amounts of electronic waste. The EU's Circular Economy Action Plan and the waste hierarchy have influenced the strategies of member states, with varying impacts on resource and energy productivity (Ghisellini et al., 2016). Hartley et al. (2020) found that countries with stricter waste prevention policies and well-developed recycling infrastructure generally performed better in terms of resource productivity, although the benefits for energy productivity were more inconsistent.

The existing knowledge depicts that resource productivity plays a key role in sustainable development and economic growth. Different resources have major roles in themselves, such as water, energy, and materials. Many studies have been checking the impact of resource productivity on economic growth, innovation, and sustainability. These studies have considered waste as the passive variable. Furthermore, fewer researchers have studied the impact of all resources (water, energy, and material) separately. By considering these limitations, the study takes waste generation as well as waste treatment as independent variables and analyses its impact on not only resource productivity but also its sub-part energy productivity, also in the EU. No earlier study has taken both variables in the same study in this way. The EU is a group of countries that has made resource productivity one of the sustainable development indicators to attain sustainability. It is going well in this direction, but there is a lot more to do in the EU to achieve this goal. In Western Europe, countries like Germany, Belgium, and Austria, with recycling rates above 50% show a strong positive link between waste treatment and resource productivity. These nations have achieved 15–20% improvements in resource productivity over the past decade (Domenech & Bahn-Walkowiak, 2019). However, the impact of waste management on energy productivity is more complex. Waste-to-energy plants in countries like Sweden and Denmark, while contributing to material recovery, also consume significant energy, which can influence national energy productivity metrics. Farooq et al. (2021) reported that Swedish waste-to-energy plants require between 30-45 kWh of energy per ton of waste processed, though some of this is offset by the energy recovered during incineration.

3. DATA AND METHODOLOGY

This section describes the data sources and methods used in the analyses.

3.1. Data

The choice of variables is informed by the empirical regularity. In the last few years, the EU has seen many changes in the amount of waste generation and waste treatment. This research highlights the importance of a circular economy in achieving higher resource productivity by showing waste generation to waste treatment processes in the EU. The annual data is obtained from the World Bank and Eurostat from 2004 to 2022 for 27 EU countries. The data includes as dependent variables Resource productivity (REP) (Taušová et al., 2022) and Energy productivity (ENP) (Petkovic et al., 2022). Independent variables are Waste generation (WTG) (Kumar & Samadder.,2017) and Waste treatment (WTT). Gross Domestic Product (GDP) and Population (POP) are taken as control variables.

Table 1

Description of variables

Variable	Source	Code
Resource productivity	https://ec.europa.eu/eurostat/data/database	REP
Energy productivity	https://ec.europa.eu/eurostat/data/database	ENP
Waste Generation	https://ourworldindata.org/	WTG
Waste treatment	https://ourworldindata.org/	WTT
Population	https://databank.worldbank.org/source/world-development-indicators	POP
Gross domestic product	https://databank.worldbank.org/source/world-development-indicators	GDP

3.2. Methodology

The study uses panel regression with a fixed effect model to test the relationship between independent and dependent variables. The study applies the Levin-Lin Chu test, Im Pesaran and Shin W-stat, and ADF-Fisher chi-square test to check stationarity. Additionally, the research utilizes the Westerlund test and Pedroni test to check the long-run relationship among variables.

3.2.1. Panel regression

Panel data models address heterogeneity or individual effects that may or may not be detected by looking at group (individual-specific) effects, time effects, or both (Hill et al., 2023). These impacts might be categorized as random or fixed. This study utilizes a fixed effect model after performing the Hausman test because the difference in coefficients is systematic and explanatory variables are correlated to error terms (Franzen & Bahr, 2023). Assuming uniform variance and identical slopes for each individual (group and entity), a fixed group effect model investigates variations in intercepts amongst individuals. Furthermore, the error term may be correlated with other regressors since an individual-specific effect is time-invariant and regarded as a component of the intercept (Bell & Jones, 2015). The least squares dummy variable (LSDV) regression and within-effect estimating techniques are used to estimate this fixed effect model. For robustness of results the study uses tw0-step system GMM. The base model for the study is:

$$\text{REP} = f(\text{WTT, WTG, GDP, POP}) \tag{1}$$

$$\text{ENP} = f(\text{WTT, WTG, GDP, POP}) \tag{2}$$

Where REP, ENE, and GHG are dependent variables. WTT and WTG are independent variables. GDP and POP are control variables.

The panel regression model is shown in the following equations:

$$\text{REP}_{it} = \alpha+\beta_1\text{WTG}_{it}+ \beta_2\text{GDP}_{it+} \beta_3\text{POP}_{it}+u_{it} \tag{3}$$

$$\text{REP}_{it} = \alpha+\beta_1\text{WTT}_{it}+ \beta_2\text{GDP}_{it+} \beta_3\text{POP}_{it}+u_{it}$$

$$\text{ENP}_{it} = \alpha+\beta_1\text{WTG}_{it}+ \beta_2\text{GDP}_{it+} \beta_3\text{POP}_{it}+u_{it} \tag{4}$$

$$\text{ENP}_{it} = \alpha+\beta_1\text{WTT}_{it}+ \beta_2\text{GDP}_{it+} \beta_3\text{POP}_{it}+u_{it}$$

Where REP_{it}, ENP_{it}, and GHG_{it} (cross-sectional units at a specific time) are dependent variables. WTG_{it} and WTT_{it} are independent variables. An α is the intercept, β_1 is the coefficient of WTG and WTT, β_2 is the coefficient of GDP, β_3 is the coefficient of POP, and u_{it} is an error term.

3.2.2. Cross-sectional dependence test

The study employs the CD test by Pesaran, (2004) to check cross-sectional dependence (CSD) among variables. Cross-sectional dependence occurs when observations from different units in a panel dataset are correlated, usually due to shared impacts or interactions. The null hypothesis of the test implies CS independence (Pesaran, 2021). Due to the presence of CSD, the study utilizes Driscoll-Kraay standard errors (DKSE) to account for by providing robust standard errors that correct for such dependence.

3.2.3. Panel unit-root test

The unit-root test is used to check stationarity. The study uses the Levin-Lin Chu test, Im Pesaran and Shin W-stat, and the ADF-Fisher chi-square test. Using multiple tests allows for a more comprehensive and robust assessment of stationarity by addressing the potential limits of any single method. The LLC test yields insights under homogeneous assumptions (Levin et al., 2002), whereas the IPS and ADF-Fisher tests account for heterogeneity and offer greater flexibility (Maddala & Wu, 1999). By including a lag, intercept, and trend, these tests ensure robustness against serial correlation and deterministic trends (Herranz, 2017). The null hypothesis (Ho) states that all panels have a unit root, while the alternative hypothesis suggests that the panels are stationary (Pesaran, 2012). Because all p-values for all independent variables are less than 0.05, Ho is rejected, implying that the stationarity assumption applies to all independent variables (Herranz, 2017).

3.2.4. Panel co-integration

The panel cointegration test is used to check whether the variables have a long-run stable relationship or not. The study uses the Westerlund test and Pedroni test to check the long-run relationship among variables. The Westerlund test for cointegration is particularly useful as it accounts for potential cross-sectional dependence and allows for heterogeneity across panels (Westerlund et al., 2015). The Pedroni test adds to this technique by examining cointegration using residual analysis, providing a full investigation across various dimensions of the panel. Using these two tests allows a thorough and nuanced assessment of long-run interactions, with each method capturing unique features of cointegration.

3.2.5. Autocorrelation

Autocorrelation refers to the correlation of a variable with its own past values, indicating that error terms are not independent over time. To examine the presence of serial correlation in the panel data, the Wooldridg test for autocorrelation is employed, which is widely used for its suitability in panel frameworks (Wooldridge, 2002).

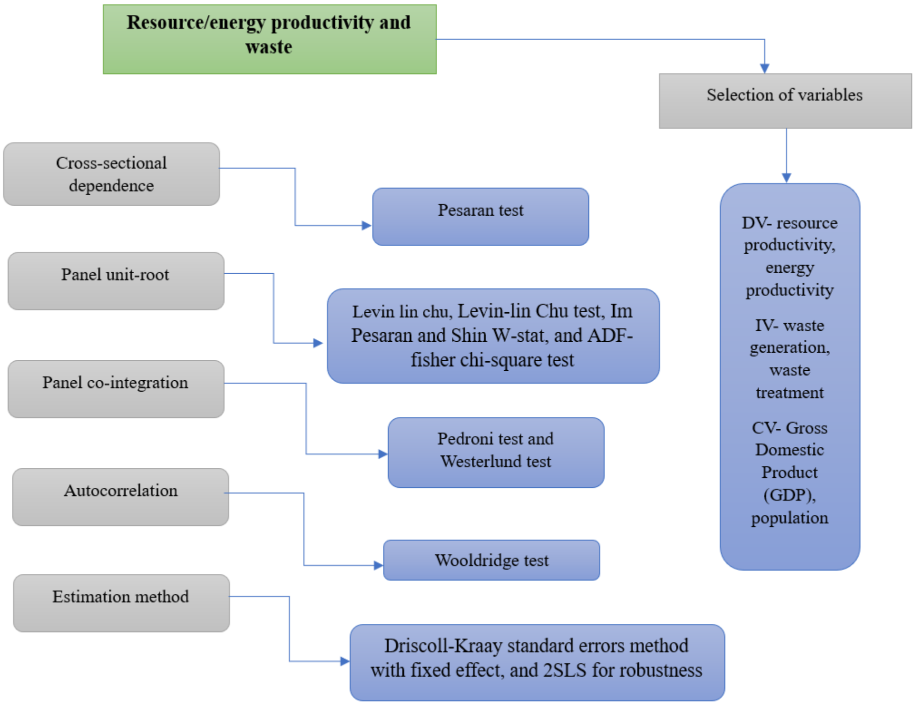

Figure 1. Methodology
Source: author's contribution

4. EMPIRICAL RESULTS

Results show the descriptive statistics of the data and the correlation among variables. Additionally, it includes test results for stationarity, cointegration, and multicollinearity.

4.1. Descriptive statistics

The descriptive statistics for the variables in this study are summarized in Table 2.1. REP has a mean value of 0.297 and a median of 0.212, with a standard deviation of 0.668, indicating some variability around the average. ENP has a mean value of 1.78 and a median of 1.81, with a standard deviation of 0.47. WTG shows a mean value of 17.27 and a median of 17.16, with a standard deviation of 1.58. WTT has a mean of 17.121 and a median of 16.930, with a standard deviation of 1.626. The distribution of WTT is also slightly negatively skewed (-0.209) with a kurtosis of 1.925. GDP has a mean value of 26.191 and a median of 26.334, with a standard deviation of 1.413. POP has a mean value of 15.805 and a median of 15.95, with a standard deviation of 1.353. The distribution of POP shows slight negative skewness (-0.463) and a kurtosis of 2.561.

The correlation matrix (See Table 2.2) reveals several significant relationships among the variables. REP has a strong positive correlation with energy productivity (ENP) at 0.745. ENP has weak positive correlations with WTG at 0.083 and WTT at 0.095. Furthermore, WTG and WTT are almost perfectly correlated (0.994) and show strong positive correlations with POP (0.84 and 0.815) and GDP (0.841 and 0.825), suggesting increased waste activities are associated with higher population and GDP. POP and GDP also have a very strong positive correlation (0.946), indicating that larger populations typically have higher GDP.

Table 2

Descriptive statistics and correlation matrix

2.1. Descriptive statistics						
	REP	**ENP**	**WTG**	**WTT**	**GDP**	**POP**
Mean	0.297987	1.782462	17.27456	17.12053	26.24558	15.80672
Median	0.212446	1.819699	17.16045	16.92996	26.35668	15.9532
Maximum	2.310553	3.292201	19.82069	19.77592	29.37906	18.23671
Minimum	-1.308963	0.457425	14.03763	13.80358	22.88033	12.90238
Std. Dev.	0.668700	0.473272	1.580357	1.626074	1.41443	1.353997
Skewness	-0.170908	-0.034064	-0.229213	-0.209285	0.0045653	-0.146367
Kurtosis	2.524672	2.999901	1.931314	1.931314	2.461398	2.561093
2.2. Correlation Matrix						
	REP	**ENP**	**WTG**	**WTT**	**POP**	**GDP**
REP	1.0000					
ENP	0.7455	1.0000				
WTG	0.0832	0.1293	1.0000			
WTT	0.0951	0.1339	0.9949	1.0000		
POP	0.1090	0.2007	0.8409	0.8153	1.0000	
GDP	0.3469	0.4341	0.8419	0.8256	0.9465	1.0000

4.2. Test results

In the first step, to check the cross-sectional dependence among variables, the study uses the Pesaran CD test. CD test results show cross-sectional dependence for most variables. However, POP shows no significant cross-sectional dependence (Table 3.1). To address the issue of cross-sectional dependence andautocorrelation, the Driscoll-Kraay standard errors (DKSE) method was used in the study. Furthermore, Levin-Lin-Chu, Im Pesaran, and Shin W-stat, and ADF-fisher chi-square test are utilized to check stationarity with one lag, intercept, and trend. The results show (Table 3.2) that the data is stationary for REP, ENP, WTG, WTT, and POP. Furthermore, IPS and ADF test shows stationarity for WTT and WTG which depicts means and variance do not change over time. The values for each test are significant at a 5 per cent or 1 per cent level, which rejects the null hypothesis for the presence of a unit-root in the data. Furthermore, after checking stationarity, the study utilizes cointegration tests to check long-run relationships or stability among the variables. The study applies the Westerlund and Pedroni test to check long-run stability. The Pedroni test statistics provide several tests to check cointegration, shown in Table 4. These tests are the Modified Phillips-Perron test, the Phillips-Perron test, and the Augmented Dickey-Fuller (ADF) test (Table 4.1). The results of these tests highlight that p-values are less than the significance level of five per cent and one per cent, which rejects the null hypothesis of no cointegration. To further verify the cointegration, the study implies the Westerlund test that supports long-run stability among variables (Table 4.2). The negative variance ratio indicates that the residuals of the cointegrating regression are stationary, suggesting the presence of cointegration. The test rejects the null hypothesis for no cointegration at a five per cent significance level. Moreover, the autocorrelation test indicates the presence of serial correlation. To address this issue, the study employs FEDK.

Table 3

Cross-sectional dependence and Unit-root tests

3.1. Cross-sectional dependence												
Variable	**REP**		**ENP**		**WTG**		**WTT**		**GDP**		**POP**	
CD-test	40.06***		72.13***		6.25***		3.41***		77.69***		2.81***	
P-value	0.000***		0.000***		0.000***		0.001***		0.000*		0.005***	
3.2. Unit-root tests (with lag one, intercept, and trend)												
	REP		**ENP**		**WTG**		**WTT**		**GDP**		**POP**	
	statistics	p-value	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value
Levin, Lin & Chu	-3.223***	0.000***	-3.2168***	0.000***	-6.3276	0.000***	-6.2893***	0.000***	1.5526	0.9397	-5.3997	0.000***
Im, Pesaran and Shin W-stat	0.6840	0.7530	6.4227	1.0000	-1.9069***	0.0283**	-1.7495***	0.0401***	10.2224	1.0000	5.4142	1.0000
ADF - Fisher Chi-square	63.4832	0.1769	12.6725	1.0000	88.0019***	0.002***	92.0413***	0.001***	3.6471	1.0000	44.5871	0.8158

Note: asterisk signs ***, **, and * are utilized for 1%, 5%, and 10% significance levels

Table 4

Pedroni test and Westerlund test for cointegration and Woolridge test for autocorrelation

4.1. Pedroni test				
	REP		**ENP**	
	Test statistic	p-value	Test statistic	p-value
Modified Phillips-Perron t	4.0818***	0.000***	2.9931**	0.0014***
Phillips-Perron t	-11.3647***	0.000***	-8.5405***	0.000***
Augmented Dickey-Fuller t	-11.5344***	0.000***	-8.4485***	0.000***
3.2. *Westerlund test*				
	REP		**ENP**	
Variance ratio test	-2.2896		-2.1173	
p-value	0.0110***		0.0171***	
3.3. Wooldridge Autocorrelation test				
	REP		**ENP**	
F-Stat	34.911		33.879	
P-value	0.0000***		0.0000***	

Note: asterisk signs ***, **, and * are utilized for 1%, 5%, and 10% significance levels)

Multicollinearity

This arises when there is a significant correlation between two independent variables in the regression model. Multicollinearity can impair the statistical power of a regression model by making it difficult to identify significant independent variables using p-values. The Variance Inflation Factor was used to measure multicollinearity. Multicollinearity occurs when the VIF value is more than 10 (Table 5).

Table 5

Multicollinearity

Variable	**VIF**	**1/VIF**	**Variable**	**VIF**	**1/VIF**
GDP	8.33	0.12005	GDP	8.48	0.11792
POP	8.27	0.12092	POP	7.96	0.12563
WTG	3.67	0.27247	WTT	3.25	0.31056
Mean VIF		6.75	Mean VIF		6.56

4.3. Driscoll-Kraay standard errors with fixed effects

The study chooses FEM after applying the Hausman test indicates that exogenous variables correlate with error terms. To determine how economic development and increasing/decreasing population affect the impact of WTG and WTT on REP and ENE, the study considers GDP and population as control variables. The study utilizes the Regression with Driscoll-Kraay standard errors with fixed effects. This model is utilized when the assumptions of heteroskedasticity, cross-sectional dependence, and serial correlation are violated. The study follows the sequence mentioned in Table 6:

Table 6

Structure of relationships among variables

	DV	**IV1**	**IV2**	**CV1**	**CV2**
1st relationship	REP REP	WTG	WTT	GDP GDP	POP POP
2nd relationship	ENP ENP	WTG	WTT	GDP GDP	POP POP

4.3.1. 1st Relationship

This section examines the impact of waste generation and waste treatment on Resource productivity by considering the GDP and population as control variables (Table 7.1). The study utilizes the Regression with Driscoll-Kraay standard errors to assess the results. The first stage is to analyze the impact of waste generation. The analysis shows waste generation has a significant negative impact on resource productivity. One log unit increase in waste generation leads to a 0.204 log unit decrease in Resource productivity and vice versa. Economic development and population also play a crucial role in determining the efficiency of resources. The results show that GDP and population have a significant positive impact on Resource productivity. One log unit increase in population leads to a 0.658 log unit increase in Resource productivity. Furthermore, one log unit increase in GDP causes a 0.371 log unit increase in Resource productivity and vice versa.

In the second trial, the study assesses the impact of waste treatment on resource productivity by taking GDP and population as control variables. The analyses depict that waste treatment has a significant negative impact on REP. One log unit increase in waste treatment causes a 0.161 log unit decrease in Resource productivity and vice versa. The results show that GDP and population have a significant positive impact on Resource productivity. One log unit increase in GDP causes a 0.380 log unit increase in REP and vice versa. On the other hand, one log unit increase in population leads to a 0.595 log unit increase in REP.

4.3.2. 2nd relationship

However, energy productivity is part of Resource productivity (Table 7.2). The study checks the impact of waste generation and waste treatment on energy productivity individually. In the first step, the study analyzes the relationship between waste generation and ENP by considering GDP and population as control variables. Waste generation has an negative significant impact on energy productivity. Economic development energy productivity positively, and population affects ENP negatively. One log unit increase in population causes a decrease of 0.0708 log unit increase in energy productivity and vice versa. Similarly, one unit increase in GDP results in a 0.503 log unit increase in energy productivity.

In another step, the study highlights the role of waste treatment in influencing energy productivity. Waste treatment has a statistically negative significant impact on energy productivity. The analysis indicates that a one-log-unit increase in waste treatment results in a 0.035 log-unit decrease in energy productivity. and Population have a negative impact on ENP. Furthermore, GDP significant positive impact on ENP.

One log unit increase in population results in a 0.082 log unit decrease in energy productivity. On the other hand, one log unit increase in GDP causes a 0.505 log unit increase in energy productivity.

Table 7

Relationships 1 and 2 (Regression with Driscoll-Kraay standard errors)

7.1. Relationship- 1 (REP and WTG with CVs/ REP and WTT with CVs)										
REP	Coeff.	Std. er.	t-stat	p-value		REP	Coeff.	Std. er.	t-stat	p-value
WTG	-0.204	0.0298	-6.82	0.000***		WTT	-0.161	0.0311	-5.18	0.000***
GDP	0.371	0.0224	16.58	0.000***		GDP	0.381	0.0273	13.97	0.000***
POP	0.659	0.1239	5.32	0.000***		POP	0.595	0.0987	6.03	0.000***
Cons	-16.33	1.9024	-8.58	0.000***		Cons	-16.345	1.7944	-9.11	0.000***
Within R^2 0.4106		F-stat 0.000***				Within R^2 0.3997		F-stat 0.000***		
7.2. Relationship-2 (ENP and WTG with CVs/ ENP and WTT with CVs)										
ENP	Coeff	Std. er	t-stat	p-value		ENP	Coeff.	Std. er.	t-stat	p-value
WTG	-0.0409	0.0185	-2.21	0.040**		WTT	-0.0349	0.01533	-2.28	0.035**
GDP	0.5034	0.0071	71.34	0.000***		GDP	0.5058	0.00701	72.14	0.000***
POP	-0.0709	0.0838	-0.85	0.409		POP	-0.0823	0.08417	-0.98	0.341
Cons	-9.6035	1.2171	-7.89	0.000***		Cons	-9.5935	1.2660	-7.58	0.000***
Within R^2 0.8576		F-stat 0.000				Within R^2 0.8573		F-stat 0.000		

Note: asterisk signs ***, **, and * are utilized for 1%, 5%, and 10% significance levels

4.4. Robustness test

To ensure the robustness of the empirical findings and to address potential endogeneity issues, the 2SLS estimation technique is employed (Table 8). While the baseline model accounts for heteroskedasticity, autocorrelation, and cross-sectional dependence. The 2SLS method is used to obtain consistent estimates in the presence of endogenous regressors by utilizing instrumental variables (Mogstad et al., 2021). Lagged values of the explanatory variables are employed as instruments in this investigation. The robustness and dependability of the primary findings are confirmed by the 2SLS estimation results, which agree with the baseline Driscoll–Kraay estimates.

Table 8

2SLS (Robustness Analysis)

8.1 Relationship-1: Resource Productivity (REP)

REP	Coeff.	Std. Err.	z-stat	p-value		REP	Coeff.	Std. Err.	z-stat	p-value
WTG	-0.1917	0.02245	-8.54	0.000***		WTT	-0.1699	0.0206	-8.25	0.000***
GDP	1.2405	0.43010	28.84	0.000***		GDP	1.2445	0.0434	28.65	0.000***
POP	-0.9819	0.04415	-22.24	0.000***		POP	-1.007	0.0437	-23.01	0.000***
Cons	-13.448	0.49763	-27.02	0.000***		Cons	-13.547	0.502	-26.95	0.000***
Wald chi2			848.73			Wald chi2			837.11	
R-squared			0.6361			R-squared			0.6330	
Root MSE			0.4032			Root MSE			0.405	

8.2 Relationship-2: Energy Productivity (ENP)

ENP	Coeff.	Std. Err.	z-stat	p-value		ENP	Coeff.	Std. Err.	z-stat	p-value
WTG	-0.1645	0.0145	-11.34	0.000***		WTT	-0.1502	0.0133	-11.30	0.000***
GDP	0.8845	0.0278	31.83	0.000***		GDP	0.8906	0.2802	31.79	0.000***
POP	-0.6417	0.0285	-22.50	0.000***		POP	-0.6623	0.0282	-23.45	0.000***
Cons	-8.455	0.3215	-26.29	0.000***		Cons	-8.5620	0.3242	-26.41	0.000***
Wald chi2			1083.67			Wald chi2			1078.02	
R-squared			0.6911			R-squared			0.6896	
Root MSE			0.26057			Root MSE			0.26121	

Note: asterisk signs ***, **, and * are utilized for 1%, 5%, and 10% significance levels

5. DISCUSSION

In the results, it is assessed that waste generation has a significant negative impact on resource productivity in EU countries because any kind of waste generation badly impacts the natural resources, including material, energy, labor, and water (Song et al., 2022). For instance, hazardous gases like carbon and methane that are released from waste cause air pollution. When this waste is thrown into the rivers, it leads to water pollution (Barkemeyer et al., 2023). Similarly, polluted air and water have a bad impact on the environment and human health, also create an obstacle to the efficient use of natural and human resources (Andronie et al., 2019). This is too costly to manage this waste without harming the environment. As per the EU Monitor, the average amount of municipal waste has increased from 2018 to 2021 in most EU countries. Whereas there was a decrease in municipal waste in Malta, Cyprus, Spain, and Romania. Furthermore, economic growth plays a critical role in the efficient use of resources (Bringezu et al., 2004). In this study, GDP is taken as the measure of economic growth that shows an increase in economic growth leads to enhanced Resource productivity and vice versa. This relationship exists because a growing economy works on innovation, research, development, and better infrastructure, such as transportation, health, education, and energy (Vuta et al., 2018). These activities lead to resource optimization and cost reduction, resulting in better Resource productivity. For instance, the carbon trading system adopted by the EU is benefiting from economic growth and optimum utilization of resources as well. In addition, the population is also a crucial factor in Resource productivity, as an increasing population leads to an increase in resource productivity. The reasons behind its increased population are an increased workforce with diverse skills and ideas, and demand expansion that helps in scaling up the economy. When demand expands, the firms increase production at a high scale, giving economies of scale and optimum utilization of resources (Volk et al., 2019). A large and diverse group of consumers puts pressure on firms or industries to make innovations in products and services that are eco-friendly (Barkemeyer et al., 2023). According to the Eurostat database, the EU highly generates waste in construction (37.5%) followed by mining (23.4%), wastewater services (10.8%), manufacturing (10.6%), household (9.4%), and the rest is generated by other economic activities (6.7%) especially in service sector (4.4%). As per the data, the amount of waste generation has increased over time in some EU countries. For instance, in Germany in 2004, the amount of waste was 364 million metric tons, which increased to 393 million metric tons in 2015, and in 2020, the amount was 402 million metric tons (the largest waste generated in the EU in 2020). Similarly, in the Czech Republic, 292 million metric tons of waste were generated, which decreased to 253 million metric tons in 2016, and 384 million metric tons in 2020. Several EU countries have succeeded in decreasing waste generation over the years, like Romania and Greece. In 2004 amount of waste generated by Romania was 369 million metric tons, but in 2020 it decreased to 172 million metric tons. Similarly, in Greece in 2004, waste generation was 333 million metric tons, which fell to 283 million metric tons in 2020. Additionally, relatively smaller EU countries producing larger amount of waste as compare to larger ones. As per the Eurostat, Finland produces an average of 20 tons of waste per inhabitant in 2020, whereas the EU average of 4.8 tons of waste was generated in 2020.

Waste treatment has negative significant impact on energy productivity. It minimizes environmental impact, reduces raw material consumption, and promotes innovation and technology development that help increase resource productivity (Song et al., 2022). This relationship exists between waste treatment and resource productivity due to several reasons. As per the European Environment Agency (EEA), the recycling rate has increased in the past years, but these rates are still half of the generated waste. In some EU countries like Portugal, Greece, Cyprus, and Romania, waste management infrastructure has not reached its potential. For instance, in Cyprus in 2019 and 2020, the amount of waste generation was 2.2 million tons, and the waste treatment amount was only 1.5 and 1.3 million tons. In Ireland, the amount of waste generated was 13 million tons in 2018, 15 million tons in 2019, and 16 million tons in 2020. However, the corresponding amounts of waste treated were 12 million tons in 2018, 13 million tons in 2019, and 14 million tons in 2020. In a few countries, the numbers are even worse. In Italy, from 2018 to 2020, waste generation was 17 million tons, but treated waste was less than 15 million tons. In addition, Portugal generated waste of more than 16 million tons but treated only 10 million tons of waste. These figures depict that the amount of waste treatment is not sufficient, as the amount of waste generation plays a major role in reducing resource productivity. Another reason for the significant negative impact is the time lag, as it generally takes time for the effects of waste treatment to reflect on resource productivity. One of the major causes of this delayed relationship is that, like other developing and developed nations, the EU consists of resource-intensive countries. The EU economies are highly active and dominant in sectors such as infrastructure, energy, construction, transport, tourism, and agriculture (Baldassarre, 2025). While these sectors provide various benefits, such as job creation and improved living standards, they also sustain economic growth at the expense of environmental health, contributing to climate change (Chen & Wang, 2024). As a result, the positive impact of waste treatment on resource productivity is often overlooked or delayed in recognition. For instance, as per the European Environment Agency (EEA), Agriculture is 11% and the energy sector is the source of more than 27% of carbon emissions in the EU. In addition, high economic costs outweigh the impact of waste treatment on resource productivity (Brunke & Blesl, 2014). It is important to treat waste sustainably. Moreover, waste treatment processes incineration, mechanical recycling, and certain chemical processes, consume more energy (Yeomans & Herberich, 2014). As per the EU monitor, Landfilling is still widespread in Eastern and Southern Europe. In Bulgaria and Malta, it exceeds 70%. In Greece, Cyprus, and Romania, it is greater than 50%; however, it is less than 50% in Spain and Portugal compared to 2017. The energy required to process, sort, transport, and treat waste might exceed the energy savings from reduced waste disposal, lowering overall energy productivity (Seslija et al., 2011). Additionally, transporting garbage to treatment facilities, particularly if they are centralized or located distant from the waste source, requires fuel and energy (Persson et al., 2014). This increased energy use may lower total energy productivity, particularly in places where waste treatment facilities are remote, impacting overall resource productivity (Streimikiene, 2015).

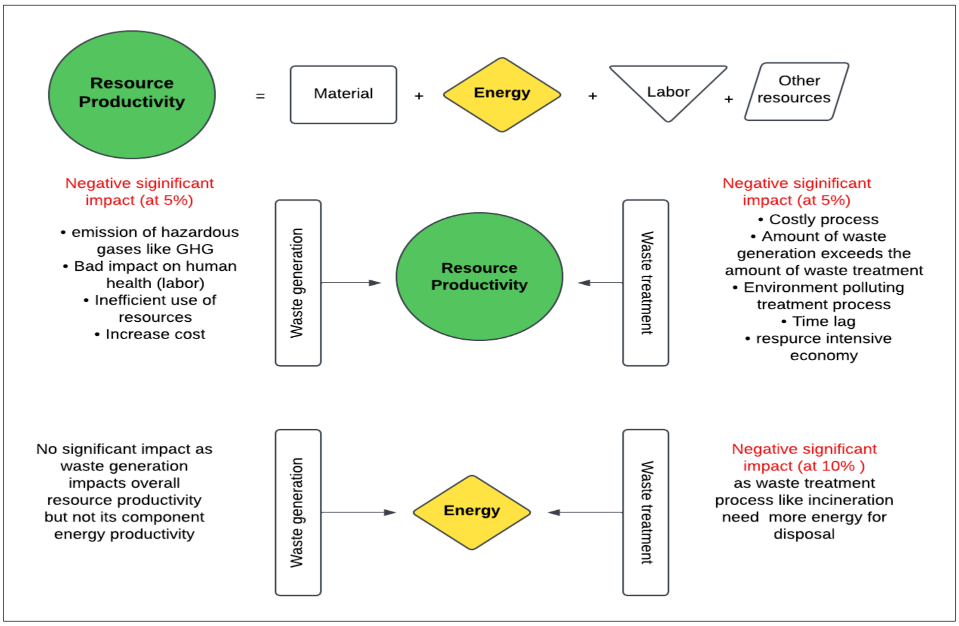

Figure 2. Waste generation and treatment: Effects on resource and energy productivity

Source- author's contribution

6. POLICY IMPLICATIONS

This study highlights the reasons that waste treatment practices do not have a significant positive impact on resource productivity and energy productivity. The research suggests numerous policy implications that can be considered by policymakers and governments in the EU. First, the focus should be prevention of waste rather than treatment by focusing on reducing waste at the source. It can be promoted by implementing a closed-loop system (Baldassarre, 2025). Closed-loop systems help reduce waste generation by converting what would otherwise be discarded into valuable inputs, improving resource productivity, and reducing the need for waste treatment (Yadav et al., 2024). This can be accomplished by creating industrial clusters that incentivize cross-industry collaboration and resource-sharing mechanisms. Introducing binding resource productivity targets for the key sector that creates hazardous waste, like infrastructure, energy, construction, transportation, tourism, and agriculture, such as circular agriculture (Vasa et al., 2017). These measures can be integrated into the EU's environmental and industrial policies that provide incentives to the entities that meet the criteria. Furthermore, to understand when and how waste treatment efforts begin to contribute and to recognize the time lag, a time-phased audit should be implemented that measures the impact over the extended periods. It will help policymakers to assess the short-term and long-term effects of waste treatment on resource productivity. Additionally, eco-tax reforms should be adopted by the government specifically for the resource-intensive sectors like construction, transportation, and energy (Chatzistamoulou & Koundouri, 2024). These taxes have to be levied on the entities that are generating waste and adopting inefficient waste prevention strategies that lead to a decline in resource productivity. Eco-taxes might encourage firms to adopt more sustainable practices (Samusevych et al., 2024) by introducing financial disincentives for industries with low resource productivity and high waste output, thereby lowering the environmental footprint of the EU's resource-intensive sectors (Vuta et al., 2018). Similarly, public and private investment in advanced waste treatment technologies enhances resource productivity and mitigates the harmful environmental impact (Zhang et al., 2017). Furthermore, green certification and labeling for businesses that are enhancing resource productivity. It will also provide a competitive advantage to the organizations by demonstrating a commitment to sustainability. Moreover, enhanced data monitoring and reporting for waste management can help researchers, policymakers, and businesses as well to measure the impact on resource productivity to inform decision-making and allow for more responsive policy adjustments. The availability of accurate, real-time data on waste and resource productivity will allow for more focused interventions and policy changes to enhance outcomes, particularly in sectors with the highest inefficiencies. Furthermore, boosting the local recycling industry approach reduces reliance on exports, improves recyclability, and protects workers during transportation. Additionally, Improved waste collection reduces contamination and increases recyclability. By focusing on waste minimization, technological innovation, regulatory frameworks, and behavioral change, the EU can improve resource productivity and achieve its sustainability goals more effectively. Moreover, there is a need for Smart city frameworks that must integrate urban planning (Slingerland et al., 2024), institutional coordination, and community engagement, promoting decentralized systems and localized resource loops rather than relying solely on centralized treatment. For instance, the European Commission supports the digital transformation of cities, also known as smart cities, to contribute to a better quality of life. These smart solutions can enhance the efficient management of resources like energy, water, and waste disposal, help monitor and reduce traffic congestion and pollution, and support the transition to greener methods for lighting and heating buildings.

7. FUTURE RESEARCH DIRECTIONS

This study contributes to the literature by defining the impact of waste on resource productivity and energy productivity separately. Additionally, this study provides some future research directions in the related research area as discussed in Table 8.

Table 9. Roadmap for future research

SR no.	Research directions	Objectives	Expected contributions
1.	Impact of waste on other resource productivity components such as material, labor, and water	To assess the impact of waste generation and treatment on resource productivity components such as material, labor, and water productivity within the framework of circular economy practices.	It will provide a more comprehensive understanding of how waste generation and treatment influence material efficiency and labor performance, offering deeper insights into the broader implications of waste management on resource utilization.
2.	Investigate the sector-specific consequences of waste generation and treatment on industries such as manufacturing, construction, agriculture, and services.	To determine how waste management strategies impact productivity, sustainability, and economic performance in these industries.	This will aid in identifying specific difficulties faced by each sector and developing focused solutions to improve waste management practices. Such insights can boost production and encourage the use of circular economy ideas in these businesses.
3.	Look into the impact of technological breakthroughs like artificial intelligence (AI), machine learning (ML), and blockchain on waste management systems.	To explore how these technologies can be leveraged to minimize the negative impacts of waste generation and treatment on resource productivity.	Waste creation can be reduced and treatment procedures made more sustainable by implementing sophisticated technology, all of which contributes to increased resource and energy productivity.
4.	Incorporation of Life Cycle Assessments (LCA) in Waste Management	Conduct a life cycle evaluation to determine the environmental and economic impact of waste treatment systems within the EU.	It supports the development of integrated waste management systems that strike a balance between sustainability and productivity.
5.	Integration of Renewable Energy in Waste Treatment Processes	Investigate the feasibility of incorporating renewable energy sources into waste treatment plants to counteract the detrimental effects on energy productivity.	The study will encourage green investments and foster energy efficiency in waste management.
6.	Land Use Planning and Urban Design for Circular Waste Flow Optimization in Smart Cities	To examine how urban spatial planning, zoning regulations, and infrastructure layout affect the efficiency of circular waste management systems and influence resource productivity in smart cities.	Insight into how compact urban forms, mixed-use zones, and decentralized waste hubs support circular waste flows.

8. CONCLUSION

The study analyses the impact of waste generation and waste treatment on resource productivity and energy productivity in EU countries. Waste treatment and waste generation have a significant negative impact on resource productivity and an insignificant impact on energy productivity, as energy productivity is a part of the resource productivity among resources like material, energy, and labor. As a part of resource productivity, energy productivity is not impacted by waste generation, but resource productivity is largely impacted by waste generation and waste treatment. The reason behind these results is that waste generation and waste treatment directly impact resource productivity as they contribute directly to material efficiency. For instance, recycling materials may minimize the energy required to create new things from raw materials. However, the magnitude of this energy saving may be small in comparison to overall energy demands, resulting in a statistically inconsequential influence on energy productivity in particular. The negative impact of waste treatment on resource productivity indicates that waste management is costly, and the amount of waste treated is too small compared to the waste generated. The study also provides the reasons why waste generation negatively impacts resource productivity. To face this problem, the implications of the study suggest various measures to enhance productivity while reducing waste generation and adopting efficient waste treatment strategies. Policy implications of the study include promoting PPP for waste treatment, investment in advanced technology for waste management that doesn't harm the environment, availability of proper data on waste so that decisions can be taken on the right to formulate policies, and mandatory sustainable reporting by corporations to the government.

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