ABSTRACT

This study investigates the institutional and financial determinants of electricity and electronic waste (e-waste) generation in the EU27, with a specific focus on the role of financial development and circular economy (CE) performance. Against the backdrop of accelerating technological diffusion and tightening environmental regulations, the research develops a novel Circular Economy Index and integrates it within a panel econometric framework to capture both linear and non-linear dynamics in waste generation. Using harmonized cross-country panel data and advanced estimation techniques such as FGLS and PCSE, including interaction modeling and threshold regressions, the study provides robust empirical evidence that well-developed financial systems contribute to reductions in e-waste when aligned with mature circular economy structures.

The empirical findings reveal that improvements in circular economy performance significantly contribute to the reduction of electricity and electronic waste, while economic expansion exhibits a waste-augmenting effect under conventional growth regimes. Evidence of non-linear threshold behavior indicates that the environmental benefits of circular economy development are contingent upon institutional maturity and systemic integration. Furthermore, interaction effects between financial development and circular economy indicators demonstrate the presence of rebound-type dynamics, whereby accelerated financial deepening can partially offset environmental gains if not aligned with circular governance standards. The study also validates the presence of a Kuznets-type non-linear relationship between income and e-waste generation under circular transition regimes. These findings provide robust policy-relevant insights for designing integrated financial and circular economy strategies to decouple waste generation from economic growth and advance the European Union’s sustainable development agenda.

Keywords: *Electricity and Electronic Waste; Circular Economy; Financial Development; Panel Econometrics; Environmental Sustainability; EU27*

JEL Classification Code: *Q53, G20, O44, C33*

CHAPTER 3: DATA AND METHODS

To rigorously test the hypotheses developed in Chapter 2, this chapter outlines the data construction process, variable definitions, and econometric methodologies employed to examine the relationship between financial development, circular economy performance, and electricity and electronic waste in the EU27. It details the procedures for data collection from harmonized international databases, the development of composite indices, and the transformation of variables to ensure statistical reliability and cross-country comparability. Furthermore, this chapter presents the panel econometric framework used in the study, including model specification, diagnostic testing, and robustness strategies, designed to address issues of heterogeneity, endogeneity, non-linearity, and cross-sectional dependence. By combining advanced panel techniques with transparent data procedures, the chapter provides a replicable and methodologically sound foundation for the empirical analysis presented in subsequent sections.

3.1. Data and Sample Selection

The research data was collected from reliable sources, specifically World Bank Data (WB), International Monetary Fund (IMF), Urban Mine Platform, and Eurostat. The data sampling process is inherited from the study of Nguyen, P. H., et al,. (2024) on the impacts related to electronic waste (E-waste). Data for the E-waste variables were collected from the Urban Mine Platform, and the circular economy (CE) was collected from European data sources - Eurostat, with CE being formed from 14 different variables (as shown in Table 3.2) and quantified using weighted entropy method and robustness by the PCA method. Financial development (FD) data was collected from the International Monetary Fund (IMF) and control variables were collected from World Bank Data.

The research period was conducted from 2010 to 2020 in 27 countries within the European region, with a total of 297 observations for each variable. The study was only conducted until 2020 due to data collection shortages, as the website for measuring WEEE or CE variables only updates until the specified period. Furthermore, the number of countries is also limited because non-European countries have not yet provided data on WEEE.

3.2. Model Specification

The authors adopt a robust econometric framework to systematically analyze the interplay between the circular economy (CE), financial development (FD), and e-waste generation (WEEE) in the EU27 countries. The primary objective of this section is to develop an econometrically sound model that accurately captures the linear, nonlinear, and interactive effects of CE and FD on WEEE, while accounting for potential threshold effects and asymmetric dynamics across varying levels of economic and financial development.

To evaluate the underlying determinants of e-waste generation, this study extends the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model (Dietz & Rosa, 1994). STIRPAT has been widely utilized to examine the drivers of environmental degradation, including carbon emissions (Shahbaz et al., 2016), energy consumption (Xu et al., 2020), and waste generation (Boubellouta & Kusch-Brandt, 2021). However, existing STIRPAT applications lack an explicit integration of circular economy mechanisms and financial development, which are essential components of contemporary sustainability transitions. Therefore, the present study enhances the STIRPAT framework by incorporating CE and FD as core explanatory variables, while controlling for relevant macroeconomic and demographic factors. This modification aligns with prior empirical research on e-waste management (Boubellouta & Kusch-Brandt, 2022) and financial sector influences on sustainability (Abid et al., 2022).

E-waste generation (WEEE) signifies the environmental indicator, while gross domestic product (GDP) and financial development (FD) depict affluence. Population density (PDS) and both renewable energy (REC), financial development (FD) serve as population and technology. The circular economy is incorporated into the study as a primary explanatory variable due to the STIRPAT model's extensibility. Urbanization (URB) are control variables (Boubellouta and Kusch-Brandt, 2021a, 2022). The model is modified as Eq. (1):

$$WEEE_{it} = f(CEI_{it}, FD_{it}, GDP_{it}, PDS_{it}, REC_{it}, URB_{it}) \tag{1}$$

The authors utilise a two-step procedure applied to assess the volatile effects of

CE on WEEE (Hong Nham and Ha, 2022; Bianchi and Cordella, 2023; Nguyen, P. H., et al, 2024).

Subsequently, to assess the aggregate effect of the circular economy, this study towards an evaluation index system based on the improved MFCE which facilitates the application of Entropy weight method to construct the composite circular economy index (CEI) (Nguyen, P. H., et al, 2024). For the soundness of research results, PCA method enhanced serves as the second CEI index.

In order to display elasticities, the study converts the variables into natural logarithms. A 1% change in the independent variables has an impact on the dependent one (log-log model), while a one-unit change in the independent variables has an impact on the dependent one * 100 (log-dependent model), according to the derived coefficients.

$$lnWEEE_{it} = \beta_0 + \beta_1 CEI_{it} + \beta_2 FD_{it} + \beta_3 lnGDP_{it} + \beta_4 lnPDS_{it} + \beta_5 lnREC_{it} + \beta_6 URB_{it} + \varepsilon_{it} \quad (2)$$

Equation (2) depicts the direct effect of the circular economy, financial development and control variables on e-waste generation. Where the subscripts i and t refer to countries and periods, respectively. β_0 is the constant term. β_1, $\beta_2 \sim \beta_6$ denote the coefficients of different variables. ε_{it} is the error term.

This baseline model examines the direct effects of CE and FD on e-waste generation, while controlling for economic affluence, demographic pressure, technological factors, and urbanization dynamics.

Equations (3) and (4) are constructed to assess the different impact mechanisms which ensure econometrics senses.

While the baseline model captures linear effects, existing empirical evidence suggests that both CE and FD exhibit nonlinear dynamics in their relationship with environmental sustainability (Bianchi & Cordella, 2023). Therefore, we extend Equation (1) to account for quadratic and interaction terms, thereby testing the hypotheses that excessive CE expansion or financial development may produce diminishing or even counterproductive effects on e-waste reduction (i.e., a rebound effect).

The first nonlinear term CEI^2, the second nonlinear term FD^2 are about to validate the hypothesis that excessive CEI or FD may reverse their benefits; and interaction term CEI*FD is added to assess whether financial development strengthens or weakens CE's impact on WEEE and the combined effect of CEI and FD. This step serves as the critical step for policy implications, as it helps identify the optimal level of CEI and FD.

$$lnWEEE_{it} = \beta_0 + \beta_1 CEI_{it} + \beta_2 CEI_{it}^2 + \beta_3 FD_{it} + \beta_4 lnGDP_{it} + \beta_5 lnPDS_{it} + \beta_6 lnREC_{it} + \beta_7 URB_{it} + \varepsilon_{it} \quad (3)$$

If $\beta_2 < 0$, then CEI exhibits an inverted U-shaped effect on WEEE, meaning that beyond a certain threshold, excessive CE fails to reduce e-waste effectively.

If $\beta_2 > 0$, then the relationship follows a U-shape, implying that higher CE levels initially reduce WEEE but eventually increase it again.

$$lnWEEE_{it} = \beta_0 + \beta_1 CEI_{it} + \beta_2 FD_{it} + \beta_3 FD_{it}^2 + \beta_4 lnGDP_{it} + \beta_5 lnPDS_{it} + \beta_6 lnREC_{it} + \beta_7 URB_{it} + \varepsilon_{it} \quad (4)$$

If $\beta_3 < 0$, then CEI exhibits an inverted U-shaped effect on WEEE, meaning that beyond a certain threshold, excessive CE fails to reduce e-waste effectively.

If $\beta_3 > 0$, then the relationship follows a U-shape, implying that higher CE levels initially reduce WEEE but eventually increase it again.

$$lnWEEE_{it} = \beta_0 + \beta_1 CEI_{it} + \beta_2 CEI * FD_{it} + \beta_3 FD_{it} + \beta_4 lnGDP_{it} + \beta_5 lnPDS_{it} + \beta_6 lnREC_{it} + \beta_7 URB_{it} + \varepsilon_{it} \quad (5)$$

This interaction term tests whether financial development enhances or undermines the effectiveness of circular economy policies. If $\beta_2 > 0$, FD amplifies CE's impact on WEEE; if $\beta_2 < 0$, FD weakens CE's effectiveness.

The study further integrates the EKC hypothesis into the STIRPAT framework by including GDP quadratic terms to capture the well-documented inverted U-shaped relationship between affluence and environmental degradation (Grossman & Krueger, 1995; Halkos & Paizanos, 2016). To examine the systematic insights from the panel data, the authors also revalidates the Environmental Kuznets Curve (EKC) concerning the presence of CEI and FD (Javid, M., & Sharif, F,2016; Akca, H., 2021) by adding the square term of lnGDP to Equations. (2), (3), (4) and (5).

It is worthy to notice that, based on the EKC hypothesis itself, economic growth can have a nonlinear relationship with environmental degradation, which is not captured by the standard STIRPAT model. To account for this, STIRPAT model and EKC hypothesis can be merged by including GDP per capita square in the STIRPAT expression (Shahbaz et al., 2016; Xu et al., 2020) which further titled extended STIRPAT (Boubellouta, B., Kusch-Brandt, 2023). Previous research has evidenced the inverted U-shaped relationship between economic growth and e-waste generation (Boubellouta and Kusch-Brandt, 2022, 2021b, 2021a, 2020; Nguyen, P. H., et al, 2024). Thus, Equations. (6), (7), (8) and (9) express the modified models.

$$lnWEEE_{it} = \beta_0 + \beta_1 CEI_{it} + \beta_2 FD_{it} + \beta_3 lnGDP_{it} + \beta_4 lnGDP^2_{it} + 5lnPDS_{it} + 6lnREC_{it} + \beta_7 URB_{it} + \varepsilon_{it} \tag{6}$$

If $\beta_4 < 0$, the relationship follows an inverted U-shape, so this is the confirmation of the EKC hypothesis.

If $\beta_4 > 0$, the relationship follows a U-shape, meaning GDP increases environmental burden indefinitely.

$$lnWEEE_{it} = \beta_0 + \beta_1 CEI_{it} + \beta_2 CEI^2_{it} + \beta_3 FD_{it} + \beta_4 lnGDP_{it} + \beta_5 lnGDP^2_{it} + \beta_6 lnPDS_{it} + \beta_7 lnREC_{it} + \beta_8 URB_{it} + \varepsilon_{it} \tag{7}$$

$$lnWEEE_{it} = \beta_0 + \beta_1 CEI_{it} + \beta_2 FD_{it} + \beta_3 FD^2_{it} + \beta_4 lnGDP_{it} + \beta_5 lnGDP^2_{it} + \beta_6 lnPDS_{it} + \beta_7 lnREC_{it} + \beta_8 URB_{it} + \varepsilon_{it} \tag{8}$$

$$lnWEEE_{it} = \beta_0 + \beta_1 CEI_{it} + \beta_2 CEI * FD_{it} + \beta_3 FD_{it} + \beta_4 lnGDP_{it} + \beta_5 lnGDP^2_{it} + \beta_6 lnPDS_{it} + \beta_7 lnREC_{it} + \beta_8 URB_{it} + \varepsilon_{it} \quad (9)$$

If $\beta_5 < 0$, the relationship follows an inverted U-shape, so this is the confirmation of the EKC hypothesis.

If $\beta_5 > 0$, the relationship follows a U-shape, meaning GDP increases environmental burden indefinitely.

The study argues that a specific CEI threshold must be achieved for a beneficial effect on WEEE. Given the disparity of circular economy development among EU27 countries, there is a suggestion of the nonlinear relationship between CEI and WEEE.

A method accounting for nonlinearity is to add a threshold effect. Therefore, following Seo and Shin (2016) and Seo et al. (2019), the study proposes a dynamic panel threshold model as Eq. (8) to capture the threshold effect of CEI and FD which enables identification of critical CEI and FD thresholds beyond which their impact on WEEE generation changes.

This approach also enables investigation of the asymmetric impacts of CEIxFD, FD, GDP, PDS, REC and URB upon different CEI thresholds.

$$lnWEEE_{it} = \beta_0 + (\beta_1 lnWEEE_{it-1} + \beta_2 X_{it}) \,.\, I\{CEI \leq \gamma\} + (\beta_3 lnWEEE_{it-1} + \beta_4 X_{it}) \,.\, I\{CEI > \gamma\} + \varepsilon_{it} \quad (10)$$

The model determines at what level CE begins to exhibit nonlinear effects, providing policy-relevant insights for optimizing CE and financial mechanisms.

The econometric framework adopted in this study is comprehensive, theoretically grounded, and methodologically rigorous, leveraging advanced techniques such as STIRPAT, interaction modeling, extended EKC, and threshold regressions. This ensures that the research findings contribute to both academic literature and practical policy discussions on circular economy strategies, financial development, and sustainable e-waste management in the EU.

3.3. Variable measurement

3.3.1 Electronic waste - Dependent variable

As mentioned above, electronic waste negatively impacts the environment if not properly managed. This is because e-waste contains specific non-degradable components such as decabromodiphenyl ether and tetrabromobisphenol A. Improper disposal can pose significant risks to human health due to the presence of hazardous elements. Common sources of e-waste in daily life include mobile phones, cameras, radios, watches, rechargeable batteries, and more. This type of waste is considered the fastest-growing due to the increasing demand for technology (Salma et al., 2023).

The impact of e-waste on the environment is evident through soil, water, air, dust, and the entire ecosystem when electronic waste is improperly recycled. According to Meng et al. (2014), plant roots can easily absorb toxic substances from heavy metals caused by e-waste, leading to crop contamination. Empirical evidence has been provided in countries such as India and China. Additionally, e-waste can generate substances that infiltrate water systems. Moreover, toxic chemicals from e-waste can also diffuse into the air through dust or smoke.

The amount of electronic waste in this study is measured by the per capita electronic waste generated each year in EU countries. The components include temperature exchange equipment (kg), screens (kg), lamps (kg), large equipment (kg), small equipment (kg), small IT (kg).

3.3.2 Circular economy - Independent variable

(i). Circular economy concept

The Circular Economy is a sustainable economic model aimed at minimizing waste and optimizing resource utilization by extending the lifecycle of products, materials, and resources. This approach represents a shift from the traditional linear economic model ("take-make-waste") to a circular system that emphasizes reuse, recycling, and resource regeneration. The CE is grounded in three core principles: eliminating waste and pollution, keeping products and materials in use, and regenerating natural ecosystems. Stahel (2016) highlights that the CE promotes designing products for durability, repairability, and recyclability, ensuring that resources are kept in the economy for as long as possible.

Empirical studies have shown the potential of the CE to drive economic, environmental, and social benefits. For example, Ghisellini et al. (2016) noted that the CE can reduce resource dependency and waste production, contributing to the mitigation of climate change. In the context of industrial applications, Kirchherr et al. (2017) emphasized that the CE supports innovative business models, such as product-as-a-service and shared consumption, which optimize the use of resources. Additionally, Korhonen et al. (2018) argued that the CE fosters sustainability by integrating renewable energy and creating closed-loop systems to reduce environmental impact.

At the EU level, a number of studies have introduced composite indices (Giannakitsidou et al., 2020; Škrinjarí, 2020; Stanković et al., 2021; Karman and Pawłowski, 2022; Ailincă et al., 2022; Banjerdpaiboon and Limleamthong, 2023; Martínez Moreno et al., 2023). Alongside its current dimensions of production and consumption, waste management, secondary raw materials, and competitiveness and innovation, the updated MFCE adds a new thematic area on global sustainability and resilience. New metrics like material footprint, resource productivity, consumption footprint, greenhouse gas emissions from production, and reliance on material imports are also included.

Existing approaches use single indicators (e.g., municipal waste recycling rates) as the works by (Magazzino et al., 2021; Tiwari et al., 2023; Wang et al., 2023), multiple indicators, or composite indices (Pao and Chen, 2022; Bianchi and Cordella, 2023; Hailemariam and Erdiaw-Kwasie, 2023)

The study improves upon past research by integrating the latest MFCE framework indicators revised by the EU in 2023 (Škrinjarí, 2020; Giannakitsidou et al., 2020; Stanković et al., 2021; Ailincă et al., 2022; Karman and Pawłowski, 2022; Martínez Moreno et al., 2023).

(ii). Operationalisation by The Entropy Weight Method (EWM)

To quantify and operationalize the level of circular economy (CE) adoption across EU27 countries, this study constructs a Composite Circular Economy Index (CEI) for the period from 2010 to 2020. The CEI serves as a comprehensive measure that captures the multidimensional aspects of circular economy performance by integrating 14 key indicators derived from the MFCE framework.

The Entropy Weight Method (EWM) is employed to objectively assign weights to these indicators, eliminating subjectivity in the weighting process (X. Li et al., 2011; Cunha-Zeri et al., 2022). This approach ensures that the information richness of each indicator is preserved, enhancing the reliability and robustness of the CEI. Higher entropy weight values indicate a greater degree of informational contribution, allowing for a more precise and unbiased representation of CE development levels across countries and time. Mathematically, the CEI is computed through a five-step process, as detailed below.

Step 1: Normalization of Indicator Data

Given that CE indicators are expressed in different units, normalization is required to ensure comparability across variables. This study employs a range transformation approach to standardize the values onto a uniform scale [0,1]. The normalization process is performed separately for benefit indicators (where higher values indicate better performance) and cost indicators (where higher values indicate worse performance). Eqs. (9), (10).

(a) Normalization for Benefit Indicators

For indicators where a higher value is desirable (e.g., circular material use rate, recycling rate, resource productivity), the standardization is performed as follows:

$$f_{ijt} = \frac{e_{ijt} - min(e_{ijt})}{\left(d_{ijt}\right) - min(d_{ijt})} \tag{12}$$

(b) Normalization for Cost Indicators

For indicators where a higher value represents greater inefficiency or environmental burden (e.g., waste generation, material footprint), the transformation is performed as:

$$f_{ijt} = \frac{\left(e_{ijt}\right) - e_{ijt}}{\left(e_{ijt}\right) - min(e_{ijt})} \tag{13}$$

Suppose there are M countries in the sample, N indicators in the index system, T years in the study period, and i = 1, 2,…, M; j = 1, 2,…, N; t = 1, 2,…, T. e_{ijt} is the j indicator value of country i in the year t. f_{ijt} is the standardized indicator value of e_{ijt}.

The standardized indicator matrix is then constructed as: $F = [f_{ijt}]_{M\times N\times T}$.

This transformation ensures that all indicators are expressed on a consistent scale, enabling the accurate computation of index weights.

Step 2: Computation of Entropy Values

The entropy measure captures the degree of variation in each indicator across countries and years, reflecting its relative informational contribution. The entropy value for each indicator is calculated as:

The index entropy value h_j is calculated by Eq. (11). $g_{ijt}.\,ln(g_{ijt})$ is set as zero if g_{ijt} is equal to zero.

$$h_j = -\frac{\sum_{i=1}^{n} g_{ijt}.ln(g_{ijt})}{ln(M.T)} \tag{14}$$

Wherein g_{ijt} is the weight of standardized indicator f_{ijt} among M countries and T years, calculated as Eq. (12).

$$g_{ijt} = \frac{f_{ijt}}{\sum_{i=1}^{M}\sum_{t=1}^{T} f_{ijt}} \tag{15}$$

Higher entropy values indicate greater uniformity in an indicator's distribution, while lower entropy values suggest greater discriminatory power in differentiating country performance.

Step 3: Calculation of Entropy Weights

The entropy weight W_j of the indicator j in the index system is calculated and determined through Eq. (13).

$$W_j = \frac{1-h_j}{\sum_{i=1}^{N} 1-h_j} \tag{13}$$

Indicators with greater variation across countries and years receive higher weights, ensuring that the most informative variables contribute more significantly to the CEI.

Step 4: Computation of the Composite Circular Economy Index (CEI)

$$CEI_{it} = \sum_{i=1}^{N} W_j . g_{ijt} \tag{14}$$

The standardised indicator matrix is multiplied by entropy weights, as indicated by Eq. (14), to determine the composite circular economy index (CEI). The larger the value, the higher the level of circular economy development.

Higher CEI values indicate a greater level of circular economy implementation (e.g., stronger recycling systems, higher material efficiency, lower waste generation).

Lower CEI values signify weaker circular economy performance, highlighting countries where linear economic practices still dominate.

(iii). Operationalisation by Principal of component analysis (PCA)

Principal Component Analysis (PCA) is a statistical technique used to reduce the dimensionality of a dataset while preserving as much variability as possible. This is achieved by transforming the original variables into a new set of uncorrelated variables called principal components, which are ordered by the amount of variance they explain in the data. The following steps outline the mathematical procedure for constructing the Circular Economy Index (CEI) using PCA:

Step 1. Data Standardization

Given a dataset *X* with *n* observations and *p* variables, the first step is to standardize the data to have a mean of zero and a standard deviation of one. This ensures that each variable contributes equally to the analysis. The standardized data matrix *Z* is obtained as follows:

$$Z_{ij} = \frac{X_{ij} - \overline{X_i}}{s_j}$$

where Xij is the value of the j-th variable for the i-th observation, X¯j is the mean of the j-th variable, and sj is the standard deviation of the j-th variable.

Step 2. Covariance Matrix Computation

Next, compute the covariance matrix Σ of the standardized data matrix *Z*:

$$\Sigma = \frac{1}{n-1} z^T Z$$

Here, Z^T denotes the transpose of Z, and Σ is a p×p symmetric matrix that describes the covariance between each pair of variables.

Step 3. Eigenvalue and Eigenvector Calculation

Determine the eigenvalues and corresponding eigenvectors of the covariance matrix Σ by solving the characteristic equation:

$$\Sigma w=\lambda w$$

where λ represents an eigenvalue and w is the corresponding eigenvector. This step identifies the directions (principal components) along which the variance of the data is maximized.

Step 4. Principal Component Selection

Sort the eigenvalues in descending order and select the top kkk eigenvalues that capture a significant portion of the total variance. The corresponding eigenvectors form the basis for the principal components. The proportion of variance explained by each principal component is given by:

$$\text{Variance Explained} = \frac{\lambda_i}{\sum_{j=1}^{p} \lambda_j}$$

where λi is the i-th eigenvalue.

Step 5. Principal Component Scores Calculation

Compute the principal component scores by projecting the standardized data onto the selected eigenvectors:

$$T = ZW$$

where T is the n×k matrix of principal component scores, and W is the p×k matrix whose columns are the selected eigenvectors.

Step 6. Circular Economy Index (CEI) Construction

The first principal component score can be used as the Circular Economy Index (CEI), as it accounts for the maximum variance in the data related to circular economy indicators. Thus, the CEI for the *i*-th observation is:

$$\mathrm{CEI}i = Ti1$$

This index provides a single composite score representing the circular economy performance, facilitating comparison across observations.

By following these steps, PCA enables the construction of a robust Circular

Economy Index that effectively summarizes the underlying patterns in the data.

3.3.3 Financial development - mechanism variable

Financial development is one of the important variables emphasized in some recent studies on the relationship between finance, economy, and environment. This is an important factor that drives economic development while promoting the consumption of clean energy and enhancing the pursuit of sustainable development goals (Shahzad and Qin, 2019). These works identify initial costs as persistent obstacles to circular economy initiatives, emphasizing the importance of research and financial feasibility in projects within this field, because building recycling business models requires significant time and costs (Beatriz et al., 2022). Beck and colleagues investigate the role of economic sectors, such as finance, in the relationship between real income, energy consumption, and climate change, or simply in the traditional EKC of countries. It is important that new alternative econometric models also receive attention from researchers.

The FD index is a widely used indicator to assess the development level of financial institutions and financial markets in terms of depth, accessibility, and efficiency (Patel and Mehta 2023). The FD index was developed by IMF experts by assigning scores based on a set of nine criteria, the higher the value of lnFD, the more developed a country's financial system is. The measurement method is as follows:

3.3.4 Control Variables

To account for key macro-structural influences, we include urbanization, economic growth, population density, and renewable energy consumption as control variables. Urbanization (lnURB) is measured as the percentage of the urban population relative to the total population, sourced from the World Development Indicators (WDI, 2024). Rapid urbanization has heightened concerns about ecological degradation through increased resource use, pollution, and electronic waste (Chen et al., 2016; Sun, 2022). Economic growth (lnGDP) is measured as the natural logarithm of real GDP per capita (constant 2015 USD), also from WDI (2024). We incorporate both lnGDP and $lnGDP^2$ to test the Environmental Kuznets Curve (EKC) hypothesis, which posits an inverted U-shaped relationship between income and environmental degradation (Cao et al., 2019). Prior studies (e.g., Kumar et al., 2017; Kush & Hills, 2017) have emphasized the role of GDP in driving e-waste generation, particularly through increased consumption of electronic goods.

Population density (PDS), defined as the number of people per square kilometre of land area, is included to capture demographic pressure on environmental systems. High-density urban areas, especially in developing economies with weak regulations, often face challenges such as air pollution, overwhelmed waste infrastructure, and urban heat islands (Glaeser, 2011). Renewable energy consumption (REC), expressed as the share of renewable energy in total final energy use, is a critical determinant of environmental sustainability. Despite rapid growth in global renewable energy use (Statista, 2023), its adoption remains lower than that of fossil fuels. However, literature confirms its positive effects on economic growth and environmental outcomes (Apergis & Payne, 2010; Bhattacharya et al., 2016). Data for PDS and REC are sourced from Eurostat and WDI (2024), respectively. Together, these variables provide a robust framework for controlling heterogeneity in our analysis of the e-waste and financial development nexus.

Table 3.1. Variable Measurement

Name	ID	Description	Unit/Measurement
E-waste	**WEEE**	Logarithm of e-waste discarded after useful life cycle (kg per capita)	Urban Mine Platform
Financial development	**FD**	FDindex	WDI - World Bank
Economic growth	**GDP**	Logarithm of GDP per capita (USD)	WDI - World Bank
Urbanization	**URB**	Urban population (% of total population)	WDI - World Bank
Population density	**PDS**	Population concentration (persons per square kilometre)	Eurostat
Renewable energy consumption	**REC**	Ratio of renewable energy consumption to total final energy consumption (%)	WDI - World Bank
Trade openness	**TO**	Ratio of exports and imports of goods and services to GDP (%)	WDI - World Bank

Circular economy	**CE**	The composite index of 14 CE indicators (index)	Eurostat
	CE_MF	Material footprint	Eurostat
	CE_RP	Resource productivity	Eurostat
	CE_MG	Generation of municipal waste	Eurostat
	CE_MR	Recycling rate of municipal waste	Eurostat
	CE_ER	Recycling rate of e-waste separately collected	Eurostat
	CE_CR	Circular material use rate	Eurostat
	CE_TR	Trade in recyclable materials	Eurostat
	CE_PI	Private investments related to circular	Eurostat
	CE_GV	Gross value added related to circular	Eurostat
	CE_PE	Persons employed in circular economy sectors	Eurostat
	CE_PA	Patents related to recycling and secondary raw materials	Eurostat
	CE_CF	Consumption footprint	Eurostat
	CE_GG	Greenhouse gas emissions from production activities	Eurostat
	CE_MD	Material import dependency	Eurostat

Source: Authors' summary.

3.4. Experimenting

Before assessing the empirical models, it is imperative to perform preliminary analysis to unveil the characteristics of the dataset. The study commences by examining descriptive, Pearson correlation analysis and then cross-sectional dependence (CD) through the CD test of Pesaran (2007). CD in panel data may stem from shared characteristics among countries, including economic-social networks, spatial correlation, and unobserved factors. Given the CD issue in the EU27 countries dataset, the Fisher type unit root test for panel data is used to ascertain data stationarity, as nonstationary would render conventional econometric estimators susceptible to spurious regression.

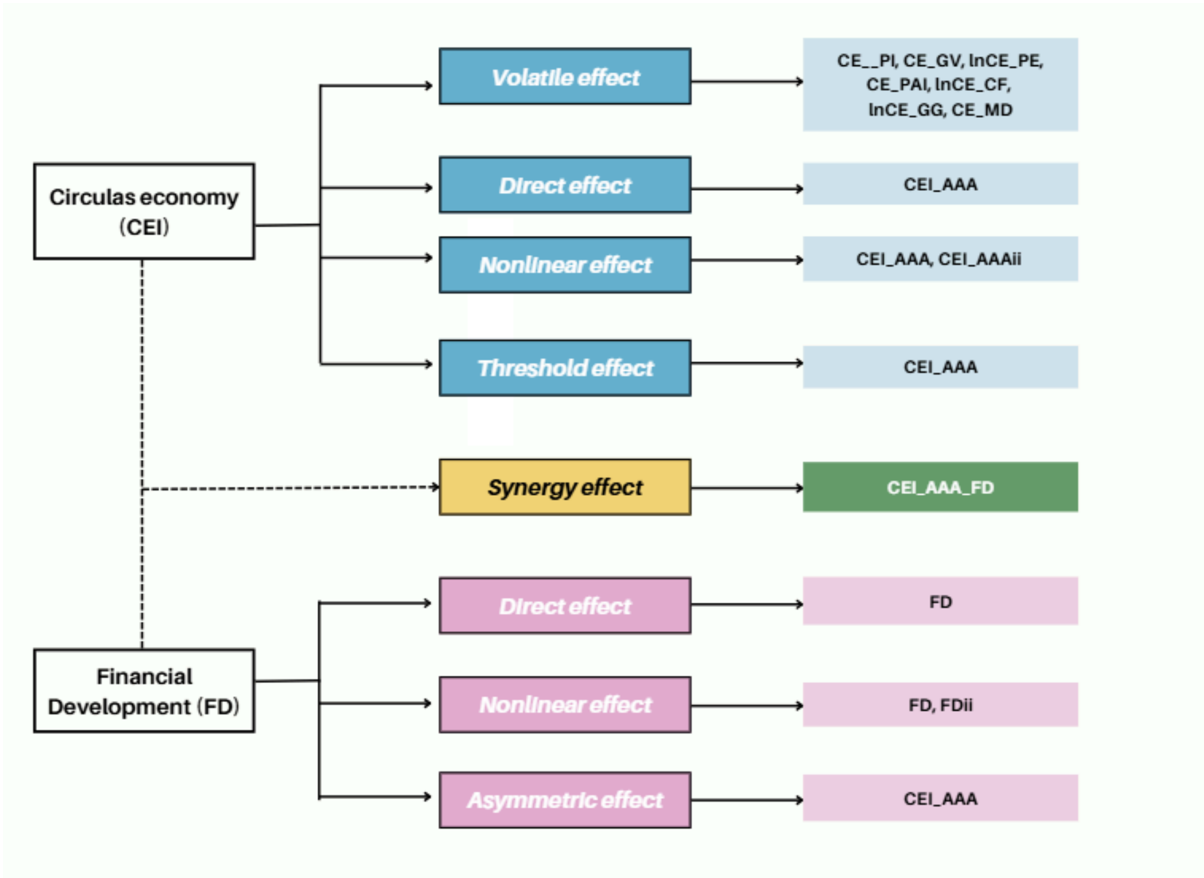
Given stationarity confirmation, the Feasible Generalized Least Square (FGLS) addresses issues of cross-sectional dependence, heteroscedasticity, and first-order autocorrelation in the static model, while Panel-corrected Standard errors (PCSE) enhance the robustness of the empirical results. The two estimation methods will perform on Eq. (2) to Eq. (9) extract insights from linear, nonlinear, synergy effects and EKC hypothesis testing.

As denoted in Eq. (10), this study employs the Dynamic panel threshold model of Seo et al. (2019) based on the GMM, including the linearity test to detect the presence of a threshold effect. This method addresses the endogeneity and simultaneity issues common in panel data analysis. Unlike the static panel threshold model of Hansen (1999) and the panel smooth transition regression model of González et al. (2005), it accommodates the lag of the dependent variable as an instrument variable and addresses the assumption of endogenous regressors. Moreover, the method is more appropriate than the dynamic panel threshold of Kremer et al. (2013) in resolving simultaneity bias when the panels are heterogeneous, especially with panel data featuring potential endogenous threshold variable and discontinuity assumption. Last, the study employs the Granger causality test of Dumitrescu and Hurlin (2012) to examine the causal relationship among the circular economy, economic growth, and e-waste generation, determining whether the causality is bidirectional, unidirectional, or no causality.

Figure 3.1 presents the conceptual research framework that guides the empirical structure of this study by illustrating the multifaceted channels through which the Circular Economy Index (CEI) and Financial Development (FD) influence electricity and electronic waste dynamics in the EU27. The model decomposes the impact of CEI into four distinct transmission mechanisms: volatile effects, which capture short-run fluctuations driven by institutional and market instability; direct effects, which reflect the immediate structural influence of circular economy practices on waste generation; nonlinear effects, which represent potential inverted U-shaped or

N-shaped relationships between circularity and waste outcomes; and threshold effects, which emphasize the existence of critical levels of circular economy maturity beyond which environmental benefits become statistically observable. The inclusion of logarithmic transformations of price-level, governance, innovation, credit, and market depth indicators ensures that both macro-financial and institutional heterogeneities are systematically embedded into the model's structure.

Figure 3.1. Proposed research model



Source: Authors' summary.

In addition, Figure 3.1 highlights the synergy effect between CEI and financial development, operationalized through interaction terms that test whether financial system depth, access, and efficiency amplify or dampen the effectiveness of circular economy mechanisms. The framework further models the direct, nonlinear, and asymmetric effects of financial development, thereby acknowledging that financial expansion may exert heterogeneous environmental impacts depending on stages of development, market maturity, and regulatory quality. By integrating asymmetric adjustment and interaction dynamics, the proposed model moves beyond linear panel specifications and enables the empirical testing of rebound effects, circularity-finance complementarities, and regime-dependent impacts. This structure provides a rigorous foundation for the dynamic panel estimations employed in subsequent chapters and ensures that both short-run volatility and long-run structural relationships are consistently identified.

CHAPTER 4: EMPIRICAL RESULTS

This chapter presents and critically interprets the empirical findings derived from the panel econometric models developed in Chapter 3. It systematically examines the linear, non-linear, interaction, and threshold relationships between financial development, circular economy performance, and electricity and electronic waste generation across EU27 countries. By integrating statistical evidence with theoretical expectations from environmental economics and sustainability transition theory, the chapter moves beyond mere coefficient reporting to uncover structural patterns, asymmetric dynamics, and institutional heterogeneity in waste management outcomes. The discussion emphasizes the economic magnitude, statistical robustness, and policy relevance of the results, thereby providing a comprehensive assessment of how financial systems and circular economy structures jointly shape environmental performance within advanced regional economies.

4.1. Preliminary analysis

4.1.1. Descriptive statistics

Table 4.1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
WEEE	297	26.165	7.417	13	42.7
CE_MF	297	18.282	8.23	0	54.707
CE_MR	297	34.571	15.534	4.1	70.3
CE_RP	297	1.726	1.042	.299	4.468
CE_MG	297	505.973	131.71	247	844
CE_ER	297	83.047	7.199	51	122.8
CE_CR	297	8.253	6.245	1.2	29
CE_TR	297	4775.345	7663.356	.1	41549.898
CE_PI	297	.67	.36	.1	2.1
CE_GV	297	1.743	.758	.5	6.3
CE_PE	297	135495.13	188324.76	1643	764770
CE_PA	297	.828	1.273	0	11.9
CE_CF	297	.932	.204	.54	1.42
CE_GG	297	7691.303	3035.273	2599.641	16336.708
CE_MD	297	38.184	18.983	9.2	91.9
FD	297	.554	.188	.2	.9
GDP	297	30678.846	21237.557	6434.55	108351
PDS	297	176.712	265.58-5	17.648	1610.41

REC	297	20.559	11.76	1.2	57.8
URB	297	72.839	12.842	52.658	98.079

Source: Authors' synthesis by Stata.

Note: This table reports the results of descriptive statistics. There are 20 variables used in this study include: Waste Electrical and Electronic Equipment (WEEE), Recycling rate of municipal waste (CE_MR), Resource productivity (CE_RP), Generation of municipal waste (CE_MG), Recycling rate of e-waste separately collected (CE_ER), Circular material use rate (CE_CR), Trade in recyclable materials (CE_TR), Private investment related to circular economy sector (CE_PI), Gross value added related to circular economy sector (CE_GV), Persons employed in circular economy sectors (CE_PE), Patents related to recycling and secondary raw materials (CE_PA), Consumption footprint (CE_CF), Greenhouse gas emissions from production activities (CE_GG), Material import dependency (CE_MD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).

Descriptive statistics for the variables utilized in the study are shown in Table 4.1 with 297 observations. These statistics include the mean, standard deviation, maximum, and lowest values of the data sample for the variables used in the study. Specifically:

In all samples, the mean value of WEEE is 26.165 kilograms, with the maximum value reaching 42.7 kilograms per person and the minimum value at 13 kilograms per person. This highlights a significant disparity in e-waste generation among EU countries. Romania recorded the highest values in the EU from 2014 to 2016, whereas Spain had the lowest values for most years.

Regarding the independent variables in the model, Financial Development Index (FD), for the 27 EU countries during the period 2010-202, the IMF assigns an average score of 0.554 points, with the highest and lowest values being 0.9 and 0.2.

In terms of control variables, the GDP per capita (constant year 2015) in each country has an average value of 30.678,846 USD. The nation having the highest value is Luxembourg, particularly 108.351 USD per capita in 2016. The nation having the lowest value is Bulgaria with 6434.55 USD per capita. The significant disparity between these two countries can be explained by the fact that Luxembourg has the highest GDP per capita due to its small population (~650,000 people) and an economy heavily reliant on high-quality financial and service sectors. In contrast, Bulgaria's economic structure still depends significantly on agriculture. For the REC variables, the average value is 20.559, showing that the renewable energy consumption rate in researched EU countries between 2010 and 2020 is 20.559% of total energy consumption. The nation having the highest value is Sweden with 57.8% of total energy consumption in 2020. The nation having the lowest value is Malta with 1,2%. The differences among countries stem from natural conditions, energy policies, and the level of investment in renewable energy within each nation. The European Union has proposed a strategy to narrow this gap by establishing a target to raise the share of renewable energy to 42.5%. The urbanization variable (URB) has an average value of 72.839%, with the highest reaching 98.079% and the lowest being 52.658%. The disparity in urbanization levels across EU countries is influenced by historical, economic, and geographic factors. Western European nations industrialized earlier, leading to higher urbanization, while Eastern European countries remained more rural due to later industrial development and economic differences.

4.1.2. Pearson correlation coefficients matrix

Table 4.2. Pairwise correlations

Variables	(weee_raw)	(CE_MF)	(CE_MF)	(CE_RP)	(CE_MG)	(CE_MR)	(CE_ER)	(CE_CR)	(CE_TR)	(CE_PI)	(CE_GV)	(CE_PE)	(CE_PA)	(CE_CF)	(CE_GG)	(CE_MD)	(FD)	(gdp_raw)	(pds_raw)	(rec_raw)	(URB)
weee_raw	1.000																				
CE_MF	0.179	1.000																			
CE_MF	0.179	1.000	1.000																		
CE_RP	-0.167	-0.141	-0.141	1.000																	
CE_MG	-0.207	-0.041	-0.041	0.075	1.000																
CE_MR	0.037	0.113	0.113	0.593	0.051	1.000															
CE_ER	0.058	0.128	0.128	-0.058	0.020	-0.028	1.000														
CE_CR	-0.047	-0.120	-0.120	0.652	0.062	0.517	-0.206	1.000													
CE_TR	0.070	-0.284	-0.284	0.433	0.034	0.351	-0.135	0.520	1.000												
CE_PI	0.228	0.006	0.006	0.294	0.217	0.365	-0.225	0.395	0.194	1.000											
CE_GV	-0.164	-0.094	-0.094	0.050	0.077	0.107	-0.040	-0.092	-0.143	0.044	1.000										
CE_PE	-0.247	-0.271	-0.271	0.297	0.291	0.305	-0.035	0.327	0.352	-0.053	0.058	1.000									
CE_PA	-0.104	-0.128	-0.128	0.320	0.240	0.452	-0.075	0.394	0.383	0.067	0.028	0.831	1.000								
CE_CF	0.080	-0.058	-0.058	0.169	0.077	0.129	-0.055	0.451	0.168	0.217	-0.149	0.156	0.068	1.000							
CE_GG	0.131	0.279	0.279	0.202	0.058	0.217	0.023	0.161	-0.011	0.085	0.158	-0.137	0.044	0.017	1.000						
CE_MD	-0.083	-0.184	-0.184	0.799	-0.070	0.394	-0.087	0.562	0.321	0.410	-0.075	-0.050	0.040	0.215	0.199	1.000					
FD	-0.212	0.027	0.027	0.733	0.154	0.475	-0.025	0.383	0.427	0.103	0.110	0.423	0.411	-0.143	0.093	0.359	1.000				
gdp_raw	-0.004	0.370	0.370	0.765	-0.028	0.572	0.054	0.324	0.108	0.221	0.103	-0.022	0.140	-0.086	0.466	0.585	0.624	1.000			
pds_raw	-0.220	-0.267	-0.267	0.312	-0.001	-0.094	-0.135	0.255	0.147	0.301	0.093	-0.044	0.026	0.019	0.024	0.582	0.131	0.090	1.000		
rec_raw	0.201	0.467	0.467	-0.338	0.107	0.103	0.091	-0.274	-0.234	0.001	-0.125	-0.223	-0.182	0.088	-0.220	-0.432	-0.108	-0.053	-0.443	1.000	
URB	-0.167	0.121	0.121	0.539	0.037	0.308	-0.069	0.435	0.233	0.278	-0.147	0.030	0.152	0.008	0.262	0.551	0.533	0.506	0.480	-0.136	1.000

Source: Authors' synthesis by Stata.

Note: There are 20 variables used in this study include: Waste Electrical and Electronic Equipment (WEEE), Recycling rate of municipal waste (CE_MR), Resource productivity (CE_RP), Generation of municipal waste (CE_MG), Recycling rate of e-waste separately collected (CE_ER), Circular material use rate (CE_CR), Trade in recyclable materials (CE_TR), Private investment related to circular economy sector (CE_PI), Gross value added related to circular economy sector (CE_GV), Persons employed in circular economy sectors (CE_PE), *Patents related to recycling and secondary raw materials (CE_PA), Consumption footprint (CE_CF), Greenhouse gas emissions from production activities (CE_GG), Material import dependency (CE_MD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

The results of Pearson correlation analysis between the variables used in the study are presented in Table 4.2. The independent variable weee_raw shows weak and insignificant correlations with most variables, with the highest coefficient being 0.037 (with CE_MR, p>0.1). However, it negatively correlates with CE_RP (-0.167, p<0.1), indicating a weak inverse relationship. Among the circular economy-related variables, CE_RP exhibits strong positive correlations with CE_CR (0.652, p<0.01) and CE_MR (0.593, p<0.01), highlighting strong interdependencies within the circular economy framework, consistent with research expectations. The dependent variable CE_MD shows a powerful positive correlation with CE_RP (0.799, p<0.01) and CE_CR (0.562, p<0.01), emphasizing its strong link to these factors. Additionally, GDP (gdp_raw) is positively and significantly correlated with key variables like CE_RP (0.765, p<0.01) and CE_MR (0.572, p<0.01), underscoring the importance of economic growth in driving circular economy elements. Similarly, urbanization (URB) shows positive and significant correlations with CE_RP (0.539, p<0.01) and CE_CR (0.435, p<0.01), reflecting its critical role in promoting circular economy practices. Most correlations are below 0.6, indicating that the variables are suitable for regression analysis without significant multicollinearity concerns (Gujarati, 2011). However, certain strongly correlated pairs, such as CE_RP and CE_MD, warrant careful consideration to avoid endogeneity issues.

4.1.3. Cross-sectional dependence test

Table 4.3. Cross-Sectional Dependence Tests Results

	Breusch-Pagan LM	**Frees' Test**	**Friedman's Test**	**Pesaran's Test**	**CD-Test**	**P-Value**
Main empirical model	1474.885 (Pr=0.000)	7.463 (Critical: 0.2333, 0.3103, 0.4649)	144.013 (Pr=0.000)	29.669 (Pr=0.000)	-	-

weee_raw	-	-	-	-	50.966	0.000
CE_MF	-	-	-	-	4.173	0.000
CE_RP	-	-	-	-	14.239	0.000
CE_MG	-	-	-	-	-0.31	0.756
CE_MR	-	-	-	-	26.995	0.000
CE_ER	-	-	-	-	1.427	0.154
CE_CR	-	-	-	-	5.407	0.000
CE_TR	-	-	-	-	3.588	0.000
CE_PI	-	-	-	-	5.545	0.000
CE_GV	-	-	-	-	4.579	0.000
CE_PE	-	-	-	-	32.548	0.000
CE_PA	-	-	-	-	2.671	0.008
CE_CF	-	-	-	-	21.758	0.000
CE_GG	-	-	-	-	16.703	0.000
CE_MD	-	-	-	-	13.291	0.000
FD	-	-	-	-	7.767	0.000
gdp_raw	-	-	-	-	43.358	0.000
pds_raw	-	-	-	-	1.901	0.057
rec_raw	-	-	-	-	41.362	0.000
URB	-	-	-	-	35.202	0.000

Source: Authors' synthesis by Stata.

Note: There are 20 variables used in this study include: Waste Electrical and Electronic Equipment (WEEE), Recycling rate of municipal waste (CE_MR), Resource productivity (CE_RP), Generation of municipal waste (CE_MG), Recycling rate of e-waste separately collected (CE_ER), Circular material use rate (CE_CR), Trade in recyclable materials (CE_TR), Private investment related to circular economy sector (CE_PI), Gross value added related to circular economy sector (CE_GV), Persons employed in circular economy sectors (CE_PE), Patents related to recycling and secondary raw materials (CE_PA), Consumption footprint (CE_CF), *Greenhouse gas emissions from production activities (CE_GG), Material import dependency (CE_MD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

Table 4.3 shows that the null hypothesis of no cross-dependence between the elements is rejected, meaning there is a possibility of cross-dependence between the variables, except for CE_MG and CE_ER.

Due to the cross-dependence that appears among most variables in the model, the use of traditional regression methods may no longer be appropriate, as they may not control the correlation relationships among the elements in the research sample. This can lead to biased estimates and reduce the reliability of the analysis results.

To address this issue, it is necessary to apply estimation methods capable of controlling cross-dependence, such as Feasible Generalized Least Squares (FGLS) aligned with Panel-Corrected Standard Errors (PCSE). These methods help minimize standard errors, adjust the reliability of regression coefficients, and ensure accuracy in estimating the impact between variables.

4.1.4. Stationary test

Table 4.4. Fisher-type unit root test

	Inverse Chi-Squared (P)	Inverse Normal (Z)	Inverse Logit (L)	Modified Inv. Chi-Squared (Pm)
Weee-raw	249.9157	-11.7749	-13.2235	18.8520
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_MF	172.2289	-8.2920	-8.7785	11.3766
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_MR	149.3881	-6.9226	-7.2361	9.1787
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_RP	177.6454	-8.4937	-9.0488	11.8978
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_MG	96.3580	-4.1139	-4.0087	4.0759
	(0.0003)	(0.0000)	(0.0000)	(0.0000)
CE_ER	234.9020	-11.1557	-12.3836	17.4073
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_CR	161.1635	-7.3967	-7.9158	10.3118
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_TR	141.44861	-7.4032	-7.2572	8.4184
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

CE_PI	177.7753	-8.8815	-9.2235	11.9103
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_GV	164.4779	-7.9753	-8.2601	10.6307
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_PE	83.0320	-3.1951	-3.1501	2.7936
	(0.0068)	(0.0007)	(0.0010)	(0.0026)
CE_PA	221.8872	-10.8470	-11.7254	16.1550
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CE_CF	105.3726	-3.8716	-3.9566	4.9433
	(0.0000)	(0.0001)	(0.0001)	(0.0000)
CE_GG	80.8786	-1.0109	-1.1317	2.5864
	(0.0140)	(0.1560)	(0.1299)	(0.0048)
CE_MD	166.5308	-7.5634	-8.0283	10.8283
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FD	197.2569	-9.5253	-10.2768	13.7849
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gdp_raw	121.9890	-5.2140	-5.3749	6.5422
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pds_raw	46.1913	8.1988	9.2268	-0.7514
	(0.7661)	(1.0000)	(1.0000)	(0.7738)
Rec_raw	145.6815	-6.8543	-7.0871	8.8221
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
URB	315.6065	-7.8327	-12.0502	25.1731
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Source: Authors' synthesis by Stata.

Note: There are 20 variables used in this study include: Waste Electrical and Electronic Equipment (WEEE), Recycling rate of municipal waste (CE_MR), Resource productivity (CE_RP), Generation of municipal waste (CE_MG), Recycling rate of e-waste separately collected (CE_ER), Circular material use rate (CE_CR), Trade in recyclable materials (CE_TR), Private investment related to circular economy sector (CE_PI), Gross value added related to circular economy sector (CE_GV), Persons employed in circular economy sectors (CE_PE), Patents related to recycling and secondary raw materials (CE_PA), Consumption footprint (CE_CF), Greenhouse gas emissions from production activities (CE_GG), Material import dependency (CE_MD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).

This study is conducted based on time series data in tabular form; therefore, determining the stationarity of the data is crucial. The author conducted a panel unit root test on all variables. The Fisher-type unit root test was employed using three different statistical methods: Chi-Squared test (P), Inverse normal test (Z), Logit test

(L), and Modified Inverse Chi-Squared test (Pm) which are based on the following hypotheses: H_0: The series is non-stationary and H_1: The series is stationary.

Table 4.4 indicates all the variables have p-value = 0.0000 across all testing methods. Therefore, the authors can reject the null hypothesis of the unit root test. The variables are stationary at the base order. In other words, the variables in the research model are stationary at I(0).

4.1.5. Heteroskedasticity, Autocorrelation and Multicollinearity detection

Table 4.5. Multicollinearity test

Variable	VIF	1/VIF
CE_RP	20.84	0.047992
gdp_raw	11.57	0.086593
CE_MD	11.32	0.088328
FD	5.76	0.173356
rec_raw	3.62	0.276091
CE_MR	3.62	0.276437
CE_CR	3.36	0.297877
CE_PE	3.30	0.302611
pds_raw	3.21	0.311601
CE_PA	2.82	0.354899
URB	2.79	0.358095
CE_GG	2.48	0.403835
CE_CF	2.34	0.426597
CE_TR	1.93	0.518493
CE_PI	1.63	0.614090
CE_MG	1.51	0.661899
CE_GV	1.51	0.661940
CE_ER	1.13	0.881067
Mean VIF	**4.72**	

Source: Authors' synthesis by Stata.

Note: There are 20 variables used in this study include: Waste Electrical and Electronic Equipment (WEEE), Recycling rate of municipal waste (CE_MR), Resource productivity (CE_RP), Generation of municipal waste (CE_MG), Recycling rate of e-waste separately collected (CE_ER), Circular material use rate (CE_CR), Trade in recyclable materials (CE_TR), Private investment related to circular economy sector (CE_PI), Gross value added related to circular economy sector (CE_GV), Persons employed in circular economy sectors (CE_PE), Patents related to recycling and secondary raw materials (CE_PA), Consumption footprint (CE_CF), Greenhouse gas emissions from production activities (CE_GG), Material import dependency (CE_MD), *Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

The assessment of multicollinearity for the empirical model before regression is presented in Table 4.5 through the Variance Inflation Factor (VIF), which detects the degree of correlation between a variable and the remaining variables. If VIF < 5: The level of multicollinearity is low and acceptable; 5 ≤ VIF ≤ 10: Multicollinearity may exist and requires further investigation; VIF > 10: Severe multicollinearity is present and needs to be addressed (Dormann et al., 2013).

According to Table 4.5, the variables CE_RP, gdp_raw, and CE_MD all have VIF > 10, indicating the presence of severe multicollinearity, which necessitates remedial measures. The variable FD (VIF = 5.76) falls within the range of 5 to 10, suggesting further investigation is required. The remaining variables all have VIF < 5, indicating no significant multicollinearity issues. Considering the mean VIF value of 4.72, which is below 5, further attention should still be paid to the variable CE_RP.

Table 4.6. Autocorrelation test

Wooldridge test	Results
Weee_raw	F(1,269 = 31.944
	Prob > F = 0.0000

Source: Authors' synthesis by Stata.

To test for autocorrelation, the Wooldridge test is conducted with the following hypotheses: H_0 There is no first-order autocorrelation (First-order autocorrelation does not exist), H_1: There is first-order autocorrelation (First-order autocorrelation exists). Table 4.5 shows that the p-value is 0.0000 < 0.05; therefore, the null hypothesis (H0) is rejected. We conclude that autocorrelation exists in this model.

Table 4.7. Heteroskedasticity test

Modified test	Results
Weee_raw	Chi2(1) = 0.41
	Prob > Chi2 = 0.5233

Source: Authors' synthesis by Stata.

To examine the presence of heteroskedasticity in the model, the Breusch-Pagan test is conducted with the following hypotheses: H_0: The error variance is constant (homoscedasticity), H_0: The error variance is not constant (heteroskedasticity).

Table 4.7 shows that the Chi-squared value is 0.41, and the p-value is 0.523 > 0.05. Therefore, we fail to reject the null hypothesis (H0). Consequently, there is no statistical evidence to confirm the presence of heteroskedasticity in the model.

4.2. Empirical results

4.2.1. Volatile effects of CE determinants on WEEE

Table 4.8. Volatile effects of circular economy determinants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FD	-0.469*** (-6.11)	-0.409*** (-11.14)	-0.532*** (-6.19)	-0.610*** (-23.22)	-0.264*** (-3.08)	-0.596*** (-23.94)	-0.816*** (-30.74)
GDP	0.897*** (4.20)	0.262*** (30.81)	0.175*** (6.66)	0.123*** (14.32)	0.228*** (4.12)	0.130*** (25.74)	0.158*** (18.33)
PDS	0.177*** (14.17)	0.165*** (23.98)	0.150*** (10.56)	0.107*** (27.55)	0.083*** (6.97)	0.118*** (12.67)	0.080*** (18.70)
REC	0.210*** (13.82)	0.223*** (25.30)	0.297*** (16.14)	0.209*** (37.17)	0.127*** (6.97)	0.203*** (12.67)	0.183*** (18.70)
URB	-0.102*** (-2.02)	-0.034*** (-12.61)	0.002 (0.29)	-0.082*** (-15.24)	-0.016 (-1.41)	-0.026*** (-11.72)	-0.007** (-1.99)
lnCE_MF	0.205*** (6.10)						
lnCE_RP		-0.199*** (-19.39)					
lnCE_MG			-0.160*** (-4.13)				
CE_MR				0.001*** (4.15)			
lnCE_ER					-0.859*** (-2.59)		
CE_CR						0.003*** (8.97)	
lnCE_TR							0.028***

							(20.94)
_cons	0.566** (2.54)	-0.292*** (-3.71)	1.152*** (3.24)	1.345*** (17.21)	0.651** (2.31)	1.313*** (20.05)	1.047*** (9.74)
N	296	297	297	297	297	297	297

Table 4.9. Volatile effects of circular economy determinants (Continued)

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
FD	-0.488*** (-13.68)	-0.538*** (-16.27)	-0.964*** (-2.12)	-0.593*** (-6.28)	-0.234*** (-3.54)	-0.482*** (-15.86)	-0.567*** (-13.25)
GDP	0.106*** (12.67)	0.150*** (24.28)	0.067*** (3.78)	0.196*** (6.97)	0.252*** (13.72)	0.076*** (10.27)	0.139*** (11.00)
PDS	0.067*** (8.40)	0.088*** (15.55)	0.061*** (2.66)	0.142*** (9.30)	0.175*** (5.72)	0.118*** (13.01)	0.117*** (16.61)
REC	0.172*** (25.05)	0.175*** (18.55)	0.073*** (7.37)	0.278*** (16.23)	0.078*** (5.70)	0.256*** (29.38)	0.212*** (34.12)
URB	-0.022*** (-4.48)	-0.003*** (-25.72)	-0.004*** (-4.20)	-0.0002 (-0.02)	-0.005*** (-5.28)	-0.007*** (-13.01)	-0.002*** (-9.86)
CE_PI	0.123*** (12.22)						
CE_GV		-0.059*** (-19.11)					
lnCE_PE			-0.027*** (-3.93)				
CE_PAI				-0.013 (-1.22)			
lnCE_CF					0.172***		
					(3.12)		
lnCE_GG						0.194*** (26.80)	
CE_MD							-0.0007** (-2.26)
_cons	1.688*** (21.08)	1.435*** (16.60)	2.690*** (10.19)	0.078 (0.31)	0.081 (0.39)	-0.888 (-0.80)	1.167*** (8.63)
N	297	297	297	297	297	297	297

Source: Authors' synthesis by Stata.

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. *There are 12 variables used in this study include: Private investment related to circular economy sector (CE_PI), Gross value added related to circular economy sector (CE_GV), Persons employed in circular economy sectors (CE_PE), Patents related to recycling and secondary raw materials (CE_PA), Consumption footprint (CE_CF), Greenhouse gas emissions from production activities (CE_GG), Material import dependency (CE_MD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

Financial development (FD), economic growth (GDP), population density (PDS), renewable energy consumption (REC), urbanization (URB), and circular economy factors all have different effects on environmental outcomes, as shown by the regression analysis in Table 4.8 and 4.9.

Financial development consistently exhibits a significant negative impact (coefficients ranging from -0.234 to -0.964, $p<0.01$), aligning with studies suggesting that improved financial systems can support green investments and reduce environmental degradation. GDP demonstrates a positive and significant influence across all models (coefficients ranging from 0.067 to 0.897, $p<0.01$), consistent with the Environmental Kuznets Curve (EKC) hypothesis, which posits that economic growth initially increases emissions before transitioning to a reduction phase (Grossman & Krueger, 1995). Similarly, PDS and REC have positive and significant effects, with REC's coefficients (0.073- 0.297, $p<0.01$) emphasizing its role in mitigating environmental impacts, as supported by Ghisellini et al. (2016). In contrast, urbanization predominantly exhibits a negative association, suggesting that urban efficiency and economies of scale may contribute to lower environmental burdens (Seto et al., 2012). Circular economy variables such as lnCE_MF (0.205, $p<0.01$) and CE_CR (0.003, $p<0.01$) further highlight the importance of transitioning toward sustainable practices, consistent with the findings of Geissdoerfer et al. (2017). These results underscore the multifaceted interplay between economic, demographic, and environmental factors in achieving sustainable development goals.

4.2.2. Linear effects of CEI on WEEE

Table 4.10. Linear effects of Circular economy index on WEEE

	Equation 2 by FGLS	Equation 2 by PCSE
CEI_AAA	-0.0369	-0.00697

	(-0.46)	(-0.04)
FD	-0.115**	-0.215*
	(-2.42)	(-1.77)
GDP	0.248***	0.0770
	(13.97)	(1.47)
PDS	0.163***	0.0405
	(7.51)	(1.56)
REC	0.0853***	0.105***
	(7.07)	(2.58)
URB	-0.00569***	-0.00215
	(-6.61)	(-1.53)
_cons	0.117	2.225***
	(0.69)	(3.81)
N	297	297

Source: Authors' synthesis by Stata.

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_AAA), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).

Table 4.10 shows the impact of the circular economy index (CEI) and financial development (FD) on electronic waste disposal (WEEE). Equation 2 by FGLS estimation shows the direct negative impact of the circular economy on the amount of electronic waste. By optimizing resource use, extending product life cycles, and promoting recycling. Moreover, when reusing and recycling old electronic devices, the demand for production decreases, thereby reducing the generation of electronic waste (Kara et al., 2022). According to Dantas et al. (2021), circular economy strategies such as reuse, recycling, and extending product lifespan help reduce dependence on the linear economy model, where products are discarded after use.

Furthermore, the results show that financial development has a negative impact on the amount of electronic waste, with a correlation coefficient of -0.115 at a 5% statistical significance level. This means that when financial development increases by 1 unit, the amount of electronic waste decreases by 11.5%, indicating that financial development is effective in reducing electronic waste. Studies identify initial costs as a persistent barrier to circular economy initiatives, highlighting the importance of research and financial feasibility in projects within this field, as building recycling business models requires a significant investment of time and cost (Beatriz et al., 2022). Financial development can play a crucial role in promoting a circular economy by providing flexible funding mechanisms, such as green credit, sustainable investment funds, or financial support policies aimed at reducing the initial cost burden on businesses. Additionally, Beck et al. (2022) emphasized that the financial system affects the relationship between real income, energy consumption, and climate change, thereby impacting the sustainable development of nations. This shows that a developed financial system not only supports economic growth but can also contribute to reducing environmental impact through sustainable-oriented financial policies.

The control variables GDP, PDS, REC show a positive impact on the amount of electronic waste with correlation coefficients of 0.248, 0.163, and 0.0853, all statistically significant at the 1% level. This indicates that economic growth enhances the production and consumption of electronic products, while also exacerbating environmental degradation due to the increase in electronic waste (Kusch and Hills, 2017; Awasthi et al., 2018). Furthermore, the process of urbanization has led to an increase in population in major cities, resulting in a higher demand for electronic devices due to more modern living conditions (Jianqiang Sun, 2022).

4.2.2. Non-linear effects

4.2.2.1. Non-linear effects of CEI

Table 4.11. Non-linear relationship between Circular Economy Index and E-waste

	Equation 3 by FGLS	Equation 3 by PCSE
CEI_AAA	-5.388*** (-24.57)	-5.781*** (-6.78)

CEI_AAAii	8.187*** (27.02)	8.690*** (7.36)
FD	-0.689*** (-18.32)	-0.728*** (-10.95)
GDP	0.171*** (17.96)	0.189*** (7.01)
PDS	0.0895*** (9.52)	0.0874*** (5.70)
REC	0.209*** (23.20)	0.223*** (8.08)
URB	-0.00284*** (-6.12)	-0.00208*** (-4.51)
_cons	1.866*** (15.70)	1.701*** (6.46)
N	297	297

Source: Authors' synthesis by Stata.

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_AAA), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

Table 4.11 illustrates the assessment of the non-linear impact of the circular economy. The variable CEI_AAAii has a positive significance level with a correlation coefficient of 8.187, achieving a statistical significance level of 1%, indicating a nonlinear relationship between CEI and electronic waste (WEEE). This shows that the initial development of the circular economy can help European countries reduce the amount of waste. However, when reaching a certain threshold, the continued development of a circular economy may increase the amount of electronic waste. Because circular activities no longer provide the expected benefits and may stimulate production and consumption, leading to greater pressure on the waste management system. This phenomenon can be explained through two main mechanisms.

First, the price effect occurs when the supply of secondary goods increases, leading to a decrease in product prices, thereby encouraging consumers to shop more.

This undermines the initial benefits of a circular economy, as consumer demand continues to increase instead of reducing waste. Secondly, insufficient substitutability reflects the reality that recycled products often cannot completely replace original products, leading to a trend of supplementary purchasing rather than just reuse. Especially, cheap recycled products can attract a new group of consumers, expanding the market but also increasing the total amount of electronic waste.

The consequence of excessive circular economy development can erode environmental sustainability. When the supply and demand for recycled products increase significantly, the rate of electronic device replacement also rises, creating substantial pressure on the waste collection and processing system. This requires appropriate control policies to avoid stimulating excessive consumption, while ensuring that recycled products can truly replace new products instead of merely becoming supplementary options in the market. The combination of stringent management measures, from sustainable product design to promoting a controlled circular economy, will help optimize the impact of CEI on electronic waste, ensuring that environmental benefits are not negated by the negative effects of expanded production and consumption.

4.2.2.2. Non-linear effects of FD

Table 4.12. Non-linear relationship between Circular Economy Index and Financial Development

	Equation 4 by FGLS	Equation 4 PCSE
CEI_AAA	0.606***	0.609***
	(11.75)	(7.10)
FD	2.574***	2.676***
	(18.43)	(14.71)
FDii	-2.939***	-3.132***
	(-22.28)	(-15.97)
GDP	0.0688***	0.0928***

	(5.69)	(4.39)
PDS	0.0454***	0.0506***
	(4.96)	(3.34)
REC	0.187***	0.214***
	(17.85)	(9.21)
URB	-0.00153***	-0.00123***
	(-3.73)	(-2.77)
_cons	1.273***	0.927***
	(7.84)	(3.30)
N	297	297

Source: Authors' synthesis by Stata

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_AAA), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).

Table 4.12 illustrates an assessment on the nonlinear impact of the circular economy. The variable FD has a positive significance with a correlation coefficient of - 2.939, achieving a statistical significance level of 1%, indicating a nonlinear relationship between FD and electronic waste (WEEE). The results show that financial development has a negative impact, meaning it causes an advantageous effect on the generation of electronic waste.

The development of finance allows businesses to access capital at low costs and facilitates investment in environmentally friendly projects (Lv et al., 2021). These projects not only promote sustainable development but also help reduce negative environmental impacts, including the reduction of electronic waste. For example, businesses can invest in advanced recycling technologies, improve production processes to generate less waste, or adopt sustainable product design methods, thereby reducing the amount of electronic waste generated.

Thus, the development of the financial system not only supports businesses in driving growth but also contributes to environmental protection goals, helping to reduce electronic waste through the support of eco-friendly initiatives and technologies.

4.2.3. Synergy effect of FD on the relationship between CEI and WEEE

Table 4.13. Synergy effect of FD on the relationship between CEI and WEEE

	Equation 5 by FGLS	**Equation 5 by PCSE**
CEI_AAA	-1.622*** (-6.20)	-1.469*** (-3.38)
CEI_AAA_FD	2.665*** (7.44)	2.500*** (3.92)
FD	-1.344*** (-13.45)	-1.392*** (-7.03)
GDP	0.139*** (13.43)	0.152*** (6.99)
PDS	0.109*** (12.06)	0.100*** (6.06)
REC	0.193*** (15.16)	0.226*** (8.73)
URB	-0.00238*** (-9.72)	-0.00191*** (-4.22)
_cons	1.678*** (12.59)	1.479*** (5.01)
N	297	297

Source: Authors' synthesis by Stata.

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_AAA), interaction between Circulas economy and Financial development (CEI_AAA_FD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).

The results presented in table 4.13 show that the relationship between economic and environmental factors with WEEE generation. Especially, a significant negative relationship between CEI_AAA and WEEE suggests that higher values of this variable are associated with reduced e-waste generation. CEI_AAA has a significant negative effect on WEEE, with coefficients of -1.622 and -1.469. According to Nguyen Phuc Hung, et al. (2024), higher CEI values are associated with reduced e-waste production. CEI reflects a country or region's commitment to recycling, reusing materials, and implementing sustainable production and consumption patterns. Higher CEI values indicate a more advanced circular economy, which helps in reducing electronic waste (WEEE) through several mechanisms. The European Union's WEEE Directive mandates proper e-waste collection and treatment, contributing to lower WEEE generation per capita in countries with strong CE policies (Ghisellini et al., 2016). Other factors such as FD, and URB have a negative impact on WEEE, suggesting that financial growth and urbanization may contribute to reducing e-waste, possibly through effective policies or investments in recycling systems.

Meanwhile, PDS has a significantly positive impact on WEEE, indicating that densely populated areas tend to consume more electronic devices, leading to higher e-waste production. According to Saurabh Sakhre al et, (2023) high-density regions generate more waste due to increased consumption and suboptimal waste management systems. Renewable energy consumption (REC) also has a positive relationship with WEEE, reflecting that areas with high renewable energy usage may experience an increase in electronic waste related to energy technologies. The deployment of renewable energy infrastructure requires a large number of electronic components, such as solar panels, wind turbines, and energy storage systems, which eventually contribute to e-waste. The necessity of implementing e-waste management strategies in the renewable energy sector to mitigate environmental impacts (Rania Seif, Fatma Zakaria Salem & Nageh K. Allam, 2023). GDP positively influences WEEE, implying that larger economies tend to consume more electronic products, leading to higher waste generation.

These findings align with global trends reported by the United Nations' Global E-waste Monitor, which highlights the rapid increase in e-waste generation due to technological advancements and rising demand for electronic devices (Forti, V., Baldé, C. P., Kuehr, R., & Bel, G., 2024). This underscores the need for more effective e-waste management policies, particularly in densely populated regions and areas with high renewable energy consumption.

4.2.4. EKC hypothesis validation

Table 4.14. EKC hypothesis validation

	Eq 6 by FGLS	**Eq 6 by PCSE**	**Eq 7 by FGLS**	**Eq 7 by PCSE**	**Eq 8 by FGLS**	**Eq 8 by PCSE**	**Eq 9 by FGLS**	**Eq 9 by PCSE**
CEI_AAA	-0.0126	-0.0508	-5.072***	-5.240***	-0.0186	-0.0113	-0.588**	-0.551
	(-0.22)	(-0.34)	(-29.81)	(-6.09)	(-0.17)	(-0.07)	(-2.09)	(-1.02)
FD	-0.154***	-0.302***	-0.684***	-0.694***	1.057**	0.700	-0.868***	-0.946***
	(-4.13)	(-3.60)	(-18.15)	(-10.25)	(2.56)	(1.53)	(-7.72)	(-3.66)
GDP	-0.150	1.032*	-0.709***	-0.652***	2.239***	0.167	-1.495***	-1.442***
	(-0.47)	(1.73)	(-6.10)	(-3.19)	(6.39)	(0.25)	(-14.07)	(-4.78)
GDPii	0.0110	-0.0380	0.0432***	0.0408***	-0.0941***	0.00575	0.0791***	0.0772***
	(0.71)	(-1.32)	(7.58)	(4.40)	(-5.57)	(0.18)	(15.43)	(5.32)
PDS	0.00945	0.0861***	0.0933***	0.0933***	0.169***	0.123***	0.119***	0.111***
	(0.25)	(4.06)	(7.62)	(5.84)	(4.38)	(5.69)	(12.84)	(5.87)
REC	0.0825***	0.107***	0.222***	0.229***	0.0788***	0.112***	0.206***	0.234***
	(8.20)	(5.44)	(27.07)	(7.93)	(5.79)	(3.48)	(16.25)	(8.30)
URB	-0.0012	-0.002***	-0.002***	-0.00231***	-0.000631	0.0033***	-0.0029***	-0.0024***
	(-0.94)	(-3.07)	(-6.11)	(-4.93)	(-0.32)	(2.89)	(-9.98)	(-5.34)
CEI_AAAii			7.708***	7.943***				
			(31.90)	(6.71)				
FDii					-1.067***	-1.253***		

					(-3.22)	(-2.95)		
CEI_AAA_FD							1.196***	1.177
							(3.03)	(1.44)
_cons	3.534**	-3.660	6.206***	5.882***	-11.11***	-0.273	9.717***	9.344***
	(2.21)	(-1.18)	(11.03)	(5.54)	(-6.24)	(-0.08)	(18.57)	(6.82)
N	297	297	297	297	297	297	297	297

Source: Authors' synthesis by Stata.

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_AAA), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).

Table 4.14 shows the results of equations (6), (7), (8), (9) with the aim of examining the impact of the Environmental Kuznets Curve (EKC) on circular economic development and financial development. The coefficients GDP and GDPii respectively show negative and positive values, reflecting a nonlinear relationship. Economic growth is often accompanied by increased resource extraction, industrial production expansion, and consumer demand, thereby driving the increase in electronic waste. The production and consumption of electronic devices continue to rise, increasing the amount of discarded devices when they are no longer in use, leading to greater pressure on the processing and recycling systems. However, when shifting towards a circular economy, this process creates a significant transformation, leading to a reduction in electronic waste. Countries are beginning to shift from the traditional linear economic model, where products are produced, consumed, and disposed of linearly, to an economy with less environmental impact in production and services, where products are reused, recycled, and their lifespan is extended. This not only helps reduce electronic waste but also promotes sustainable development, protects natural resources, and minimizes pollution.

Financial development is considered one of the main factors driving economic growth, and some studies have shown that financial development has a positive impact on economic growth (Jalil and Ma, 2016). At variable FD, it shows that under conditions of economic development reaching the financial development threshold, the amount of electronic waste is reduced. This result aligns with the findings of the group of authors, where the square of FD through the square of GDP promotes the reduction of electronic waste with a correlation coefficient of -1.067, -1.235 at a 1% statistical significance level. From this, it can be concluded that financial development promotes economic growth, creates favorable conditions for green development, green investment, improves the quality of equipment or production processes, and enhances recycling and reuse.

Column Eq9 shows a positive correlation with the amount of electronic waste, indicating that when economic development reaches a threshold, the circular economy becomes ineffective without timely measures. Because when economic growth reaches a threshold according to the Kuznets curve theory, people have better living conditions, leading to higher demand for electronic devices or software, which in turn results in increased electronic waste. The results in column Eq7 show a similar positive impact, which can be concluded that when the circular economy develops to a certain threshold, it will have environmental repercussions, increasing the amount of electronic waste.

However, the results also indicate evidence of the rebound effect of the circular economy, where circular practices can not only bring dual benefits in the form of "growth-growth" but can also lead to a reduction in environmental benefits as previously predicted (Zink and Geyer, 2017). These findings indicate that the adoption of a circular economy model with a low tipping point cannot guarantee that environmental impacts will always be favorable or that environmental sustainability will be enhanced. In fact, when the level of circular economy development is too high without strict control, it can have the opposite effect, increasing resource consumption and generating more electronic waste. Therefore, it is important to thoroughly assess the net impact of increased secondary production and reuse to determine whether they truly provide long-term environmental benefits. The implementation of appropriate control measures and policies will help clearly determine whether circular economy strategies truly reduce pollution, protect resources, and promote environmental sustainability as desired (Zerbino, 2022).

4.2.5. Threshold effects

Table 4.15. Endogeneity and Instrumental Variables Test

Instrumental Variables (Endogenous)	R-squared (Partial)	Robust F-Statistic	Robust score chi2(1)	p-value (First-stage regression)	p-value (chi2)	p-value (Endogeneity)	Conclusion
CEI_AAA	0.4807	73.0492	1.30615	0.0000	0.2531	0.2979	**Exogenous (Fail to reject H0)**
CEI_AAA_FD	0.5189	125.443	0.841698	0.0000	0.3589	0.3837	**Exogenous (Fail to reject H0)**
FD	0.7200	312.02	0.068172	0.0000	0.7940	0.7972	**Exogenous (Fail to reject H0)**
GDP	0.9915	30051.9	1.90443	0.0000	0.1676	0.1611	**Exogenous (Fail to reject H0)**
REC	0.9560	3034.14	1.04939	0.0000	0.3056	0.3206	**Exogenous (Fail to reject H0)**
URB	0.9998	1,200,000	23.264	0.0000	0.0000	0.0000	**Endogenous (Reject H0)**
PDS	0.9999	1,400,000	25.5159	0.0000	0.0000	0.0000	**Endogenous (Reject H0)**

Source: Authors' synthesis by Stata.

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_AAA), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

Before conducting Asymmetric analysis, it is necessary to perform IV regression (2SLS) with instrumental variables. When implementing this model, the instrumental variable needs to be exogenous. The study is conducted based on the Hansen test to determine whether the instrumental variable is endogenous or exogenous. At the same time, consider the F-statistic value to determine the strength or weakness of the instrumental variable. Through the first regression stage, the study tests the statistical significance of the instrumental variable. The results are presented in Table 4.15 as follows:

Considering the relatively high R-squared (Partial) values of the variables FD, GDP, REC, it indicates a strong explanatory power for the variation of the endogenous variable by the instrumental variables. The R-squared (Partial) values of the CEI_AAA and CEI_AAA_FD variables are relatively low (0.4807 and 0.5189), however, the F-statistic values are greater than 10, so they can be considered acceptable. Especially, the variables URB and PDS have very high values, greater than 0.99, indicating that the instrumental variable explains the corresponding endogenous variable very well.

The value of the Robust F-Statistic indicates the strength or weakness of the instrumental variable. All variables have an F-Statistic value greater than 10, especially the URB and PDS variables, which have very high values. This proves that the instrumental variables are very strong in explaining the endogenous variable.

The variables CEI_AAA, CEI_AAA_FD, FD, GDP, REC all have p-values (Chi-squared) and p-values (Endogeneity) greater than 0.01. Therefore, the null hypothesis H0 is not rejected. The above variables are all exogenous variables and can be used as instrumental variables.

The variables PDS and URB have a p-value less than 0.01. Therefore, the null hypothesis H0 is rejected. These two variables are both endogenous variables and cannot be used as instrumental variables.

In the first stage regression test, the variables CEI_AAA, CEI_AAA_FD, FD, GDP, REC, URB, PDS all have a p-value = 0.0000, indicating that all the instrumental variables are statistically significant or the instrumental variables are related to the endogenous variable.

Table 4.16. Asymmetric analysis (CEI is threshold variable)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.WEEE before	1.3631*** (0.2050)	0.7982*** (0.1147)	0.4197*** (0.1404)	1.1059*** (0.1142)	0.3005** (0.1399)	0.1617*** (0.0239)	0.7825*** (0.0796)
L.WEEE after	-1.1876*** (0.2194)	-0.9747*** (0.1768)	-1.0190*** (0.1428)	-4.1859*** (0.5018)	-1.1162*** (0.1466)	-0.1364*** (0.0310)	-0.9641*** (0.1097)
CEI_AAA before	23.5281*** (3.8366)						
CEI_AAA after	-22.8639*** (3.8249)						
CEI_AAA_FD before		1.9438*** (0.3005)					
CEI_AAA_FD after		-1.0748*** (0.2974)					
GDP before			0.7257***				

			(0.0733)				
GDP after			-0.2470*** (0.0711)				
REC before				0.0271*** (0.0104)			
REC after				0.1267*** (0.0259)			
URB before					0.0758*** (0.0039)		
URB after					-0.0192*** (0.0040)		
FD before						0.9717*** (0.2131)	
FD after						-0.9553*** (0.1709)	
PDS before							1.3122*** (0.1016)
PDS after							-0.1582*** (0.0203)
Threshold	0.2249*** (0.0028)	0.3107*** (0.0081)	0.2894*** (0.0193)	0.3838*** (0.0034)	0.2792*** (0.0086)	0.2695*** (0.0239)	0.2821*** (0.0111)
Cons	8.6240*** (1.4617)	2.8644*** (0.5017)	5.3625*** (1.0505)	13.4203*** (1.6437)	4.7422*** (0.7146)	0.8042*** (0.1364)	3.6544*** (0.4270)
Linearity test	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	297	297	297	297	297	297	297

Source: Authors' synthesis by Stata.

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_AAA), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).

The Dynamic Panel Threshold Model is utilized to further examine the asymmetric effects of variables such as CEI, CEI*FD, GDP, REC, URB, FD, and PDS on the dependent variable WEEE. These effects depend on different threshold values of the Circular Economy Index (CEI). Table 4.16 presents the results of this model, including the CEI threshold values.The coefficients of the first lag of WEEE become negative, ranging from -0.1364 to -4.1859 at a 1% significance level when surpassing the CEI threshold. This indicates that the current level of e-waste generation is influenced by its previous levels.

Column (1): Describes the symmetric effect of the circular economy on e-waste generation. The CEI threshold is 0.2249. The distribution of the CEI threshold across EU countries is presented in the table. Notably, three countries, Bulgaria, Greece, and Romania, remained below the CEI threshold from 2010 to 2020. By 2020, six countries, Bulgaria, Cyprus, Greece, Hungary, Portugal, and Romania, were still below the threshold, indicating poor environmental management quality. Column (3): Shows the asymmetric effect of GDP with a CEI threshold value of 0.2894. Before the CEI threshold, GDP positively correlates with e-waste generation, while after the threshold, the correlation becomes negative. Before the CEI threshold, low GDP indicates that economic growth is accompanied by increased investment in e-waste management systems. After the threshold, as GDP grows further, economic growth can lead to environmental challenges. Column (5): Demonstrates the asymmetric effect of national urbanization rates (URB) with a CEI threshold value of 0.2792. Before the CEI threshold, URB has a positive effect (0.0758), suggesting that urbanization contributes positively to improving the dependent variable (WEEE). After the CEI threshold, URB has a negative effect (-0.0192), indicating that urbanization might reduce effectiveness or have negative impacts on WEEE management. Column (7): Reflects the asymmetric effect of population density (PDS) with a CEI threshold value of 0.2821. Before the CEI threshold, PDS has a significant positive impact on WEEE, implying that higher population density often leads to greater efficiency in e-waste collection. After the CEI threshold, PDS shows a slight negative impact.

Column (4) does not indicate an asymmetric effect of renewable energy consumption (REC) based on the CEI threshold of 0.3838. However, the impact of REC increases gradually before and after the CEI threshold. Before the threshold (0.2171), the effect is positive and stronger compared to the effect after the threshold (0.1267). This implies that renewable energy contributes to e-waste management, but as countries surpass the CEI threshold, the effectiveness of this contribution diminishes.

In column (3), the coefficient of CEI_AAA_FD transitions from 0.3107 before the CEI threshold to a negative value (-1.0754) after surpassing the threshold. However, the coefficient after the threshold has a p-value > 0.1, indicating that it is not statistically significant. This suggests that before the CEI threshold, financial development has a positive impact on WEEE. After the CEI threshold, the negative coefficient, though not statistically significant, implies that financial development does not have an impact on WEEE management. This indicates that these countries already have stable financial systems, and further financial development does not significantly contribute to e-waste management.

Table 4.17. CEI threshold distribution

Year	High CEI (CEI_AAA > 0.2249)	Low CEI (CEI_AAA <= 0.2249)
2010	Austria, Belgium, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Ireland, Italy, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia	Bulgaria, Cyprus, Greece, Croatia, Hungary, Lithuania, Romania, Slovak Republic
2011	Austria, Belgium, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Ireland, Italy, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia	Bulgaria, Cyprus, Greece, Croatia, Hungary, Lithuania, Romania, Slovak Republic
2012	Austria, Belgium, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Ireland, Italy, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia	Bulgaria, Cyprus, Greece, Croatia, Hungary, Lithuania, Romania, Slovak Republic
2013	Austria, Belgium, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia	Bulgaria, Cyprus, Greece, Hungary, Romania, Slovak Republic
2014	Austria, Belgium, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia	Bulgaria, Cyprus, Greece, Hungary, Romania, Slovak Republic
2015	Austria, Belgium, Cyprus, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Ireland, Italy, Lithuania, Luxembourg, Latvia, Netherland, Poland, Portugal, Sweden, Slovenia	Bulgaria, Greece, Hungary, Malta, Romania, Slovak Republic

2016	Austria, Belgium, Cyprus, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia, Slovak Republic	Bulgaria, Greece, Romania
2017	Austria, Belgium, Cyprus, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia, Slovak Republic	Bulgaria, Greece, Romania
2018	Austria, Belgium, Cyprus, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia, Slovak Republic	Bulgaria, Greece, Romania
2019	Austria, Belgium, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherland, Poland, Portugal, Sweden, Slovenia, Slovak Republic	Bulgaria, Cyprus, Greece, Romania
2020	Austria, Belgium, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Croatia, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherland, Poland, Sweden, Slovenia, Slovak Republic	Bulgaria, Cyprus, Greece, Hungary, Portugal, Romania"

Source: Author's summary.

4.2.6. Bidirectional and Unidirectional effects

Table 4.18. Granger causality analysis

No.	Direction	W-bar	Z-bar	P-value (Z-bar)	Z-bar tilde	P-value (Z-bar tilde)	Decision
1	**WEEE → CE_MF**	1.7099	2.6084	0.0091	0.5752	0.5652	CE_MF → weee_raw (weak evidence)
	WEEE → CE_MF	2.4223	5.2259	0.0000	1.8972	0.0578	weee_raw → CE_MF (moderate evidence)
2	**WEEE → CE_MR**	2.4314	5.2592	0.0000	1.9140	0.0556	CE_MR → weee_raw (moderate evidence)
	CE_MR → WEEE	1.8086	2.9712	0.0030	0.7584	0.4482	weee_raw → CE_MR (weak evidence)
3	**WEEE → CE_RP**	0.7414	-0.9503	0.3420	-1.2223	0.2216	No Granger causality

	CE_RP → WEEE	5.5476	16.7091	0.0000	7.6971	0.0000	weee_raw → CE_RP (strong evidence)
4	**WEEE → CE_MG**	1.7081	2.6017	0.0093	0.5717	0.5675	CE_MG → weee_raw (weak evidence)
	CE_MG → WEEE	1.0967	0.3554	0.7223	-0.5628	0.5736	No Granger causality
5	**WEEE → CE_ER**	2.4496	5.3263	0.0000	1.9479	0.0514	CE_ER → weee_raw (moderate evidence)
	CE_ER → WEEE	2.0773	3.9584	0.0001	1.2570	0.2088	weee_raw → CE_ER (weak evidence)
6	**WEEE →CE_CR**	1.3559	1.3076	0.1910	-0.0819	0.9347	No Granger causality
	CE_CR → WEEE	2.2710	4.6700	0.0000	1.6164	0.1060	weee_raw → CE_CR (moderate evidence)
7	**WEEE →CE_TR**	1.7411	2.7229	0.0065	0.6330	0.5268	CE_TR → weee_raw (weak evidence)
	CE_TR → WEEE	3.0501	7.5325	0.0000	3.0622	0.0022	weee_raw → CE_TR (strong evidence)
8	**WEEE → CE_PI**	1.1737	0.6380	0.5234	-0.4200	0.6744	No Granger causality
	CE_PI → WEEE	1.1460	0.5363	0.5918	-0.4715	0.6373	No Granger causality
9	**WEEE → CE_GV**	.	.	.	.	.	
	CE_GV → WEEE	1.3867	1.4208	0.1554	-0.0247	0.9803	No Granger causality
10	**WEEE → CE_PE**	2.9859	7.2967	0.0000	2.9431	0.0032	CE_PE → weee_raw (strong evidence)
	CE_PE → WEEE	1.1997	0.7339	0.4630	-0.3716	0.7102	No Granger causality
11	**WEEE → CE_PA**	2.2569	4.6182	0.0000	1.5902	0.1118	CE_PA → weee_raw (moderate evidence)
	CE_PA →WEEE	.	.	.	.	.	

12	**WEEE → CE_CF**	2.1974	4.3996	0.0000	1.4798	0.1389	CE_CF → weee_raw (weak evidence)
	CE_CF → WEEE	1.4713	1.7316	0.0833	0.1323	0.8947	No Granger causality
13	**WEEE → CE_GG**	5.3811	16.0973	0.0000	7.3881	0.0000	CE_GG → weee_raw (strong evidence)
	CE_GG → WEEE	1.3219	1.1828	0.2369	-0.1449	0.8848	No Granger causality
14	**WEEE → CE_MD**	1.0078	0.0287	0.9771	-0.7278	0.4667	No Granger causality
	CE_MD → WEEE	1.9177	3.3717	0.0007	0.9607	0.3367	weee_raw → CE_MD (weak evidence)
15	**WEEE → CEI_AAA**	1.9203	3.3815	0.0007	0.9656	0.3342	CEI_AAA → weee_raw (weak evidence)
	CEI_AAA → WEEE	1.4506	1.6556	0.0978	0.0939	0.9252	No Granger causality
16	**WEEE → CEI_AAA_FD**	1.5943	2.1837	0.0290	0.3606	0.7184	CEI_AAA_FD → weee_raw (weak evidence)
	CEI_AAA_FD → WEEE	1.6539	2.4026	0.0163	0.4712	0.6375	weee_raw → CEI_AAA_FD (weak evidence)
17	**WEEE → CEI_AAAii**	1.9480	3.4833	0.0005	1.0170	0.3091	CEI_AAAii → weee_raw (weak evidence)
	CEI_AAAii → WEEE	1.4201	1.5437	0.1227	0.0374	0.9702	No Granger causality
18	**WEEE → GDP**	4.2098	11.7937	0.0000	5.2144	0.0000	gdp_raw → weee_raw (strong evidence)
	GDP → WEEE	1.0778	0.2860	0.7749	-0.5979	0.5499	No Granger causality
19	**WEEE → GDPii**	4.2719	12.0218	0.0000	5.3296	0.0000	gdp_raw_i → weee_raw (strong evidence)

	GDPii → WEEE	1.0139	0.0510	0.9594	-0.7166	0.4736	No Granger causality
20	**WEEE → FD**	1.2384	0.8760	0.3810	-0.2998	0.7643	No Granger causality
	FD → WEEE	1.9434	3.4662	0.0005	1.0084	0.3133	weee_raw → FD (weak evidence)
21	**WEEE → FDi**	1.2177	0.8000	0.4237	-0.3382	0.7352	No Granger causality
	FDi → WEEE	1.9834	3.6131	0.0003	1.0826	0.2790	weee_raw → FDi (weak evidence)

Source: Authors' synthesis by Stata.

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 20 variables used in this study include: Waste Electrical and Electronic Equipment (WEEE), Recycling rate of municipal waste (CE_MR), Resource productivity (CE_RP), Generation of municipal waste (CE_MG), Recycling rate of e-waste separately collected (CE_ER), Circular material use rate (CE_CR), Trade in recyclable materials (CE_TR), Private investment related to circular economy sector (CE_PI), Gross value added related to circular economy sector (CE_GV), Persons employed in circular economy sectors (CE_PE), Patents related to recycling and secondary raw materials (CE_PA), Consumption footprint (CE_CF), Greenhouse gas emissions from production activities (CE_GG), Material import dependency (CE_MD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).

In Table 4.18, the Granger causality test results show that some factors in the circular economy have a bidirectional relationship with e-waste, that is, WEEE not only affects the circular economy but the circular economy also has a reverse impact on the amount of e-waste (Granger, C. W. J., 1969). This shows a strong interaction between e-waste and recycling and reuse policies in the circular economy. The research results have shown that WEEE has an impact on factors in the circular economy such as CE_MR, CE_ER and CE_TR with high statistical significance (P-value < 0.05). At the same time, these factors also have a reverse impact on the amount of e-waste, although the reverse impact is weaker. Specifically, CE_MR is not only affected by the amount of WEEE but also by the amount of waste. also has a negative impact on the level of e-waste generation (P-value = 0.003). This suggests that when recycling is promoted, it can increase or decrease the amount of e-waste depending on the collection and treatment mechanism. Similarly, CE_TR has a bidirectional relationship with WEEE (P-value = 0.0022), which can be explained by the increased demand for recycled electronics, which in turn affects both e-waste and the circular economy.

In addition to the bidirectional effects, the Granger test also shows that WEEE has a unidirectional effect on many economic indicators and is not affected in reverse. Most notably, WEEE has a strong impact on GDP (P-value = 0.000), that the increase in e-waste can contribute to economic growth through collection, recycling, and resource reuse activities (Gaidajis, Angelakoglou and Aktsoglou, 2010). However, GDP does not have a significant negative impact on WEEE (P-value = 0.7749), meaning that economic growth does not necessarily increase e-waste. Similarly, another variant of GDP (GDPii) also shows that WEEE has a strong impact on the economy but not the opposite impact (P-value = 0.000 and 0.9594). In addition, WEEE also has a significant impact on some circular economy indicators such as circular economy performance (CE_PE) and green growth (CE_GG) (P-value = 0.000), but these indicators do not have a negative impact on e-waste (P-value = 0.463 and 0.2369). This suggests that although the development of the circular economy can create opportunities to optimize e-waste, it is not strong enough to automatically reduce the amount of WEEE generated. Similarly, WEEE also has an impact on CE_PA and CE_CF but not the reverse impact. For the financial sector, FD and FDi have a weak impact on WEEE (P-value = 0.0005 and 0.0003), but WEEE has no significant impact on these financial indicators (P-value = 0.381 and 0.4237). This means that finance can play a supporting role in controlling e-waste, but the extent of the impact is unclear and does not show a strong influence from WEEE on the financial market. These findings emphasise that WEEE plays an important role in the economy, especially in GDP growth, circular economy performance, and green growth, but these factors do not have a significant reverse impact on the amount of e-waste. This suggests that e-waste management policies need to be considered as part of a sustainable economic development strategy, rather than being viewed as a purely environmental issue.

4.3. Robustness check

(i). Robustness check of volatile effects using CEI_CCC

Table 4.19. Robustness check of volatile effects using CEI_CCC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FD	-0.449*** (-7.09)	-0.447*** (-5.66)	-0.549*** (-6.56)	-0.304*** (-2.57)	-0.281*** (-3.23)	-0.639*** (-9.22)	-0.862*** (-12.11)
GDP	0.605*** (3.50)	0.268*** (9.22)	0.132*** (6.58)	0.111*** (2.80)	0.235*** (7.54)	0.135*** (6.95)	0.162*** (6.53)
PDS	0.153*** (12.85)	0.163*** (8.58)	0.112*** (7.25)	0.093*** (6.51)	0.083*** (6.40)	0.106*** (7.74)	0.084*** (9.03)
REC	0.214*** (8.99)	0.230*** (8.50)	0.232*** (7.25)	0.176*** (6.51)	0.127*** (6.40)	0.225*** (9.36)	0.189*** (9.03)
URB	-0.007*** (-6.36)	-0.003*** (-5.31)	-0.002*** (-4.65)	-0.002*** (-2.09)	-0.001*** (-1.38)	-0.004*** (-4.80)	-0.008*** (-2.44)
lnCE_MF	0.202*** (7.95)						
lnCE_RP		-0.200*** (-10.00)					
lnCE_MG			-0.185*** (-3.38)				
CE_MR				0.801*** (2.60)			
lnCE_ER					-0.861*** (-2.45)		
CE_CR						0.036*** (2.68)	
lnCE_TR							0.229*** (9.49)
_cons	1.166*** (5.65)	-0.358 (-0.97)	2.312*** (7.75)	1.414*** (3.36)	0.595* (1.84)	1.225*** (4.91)	1.801*** (4.61)
N	296	297	297	297	297	297	297

Source: Authors' synthesis by Stata.

Note: ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in *parentheses. There are 12 variables used in this study include: Waste Electrical and Electronic Equipment (WEEE), Recycling rate of municipal waste (CE_MR), Resource productivity (CE_RP), Generation of municipal waste (CE_MG), Recycling rate of e-waste separately collected (CE_ER), Circular material use rate (CE_CR), Trade in recyclable materials (CE_TR), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

Table 4.20. Robustness check of volatile effects using CEI_CCC (continued)

	(8)	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
FD	-0.545*** (-9.05)	-0.617*** (-8.61)	-0.216*** (-2.49)	-0.728*** (-8.94)	-0.270*** (-2.58)	-0.439*** (-4.83)	-0.685*** (-8.59)
GDP	0.119*** (7.21)	0.164*** (7.87)	0.204*** (5.60)	0.200*** (7.19)	0.139*** (4.73)	0.066** (2.55)	0.168*** (7.10)
PDS	0.070*** (4.82)	0.102*** (7.70)	0.095*** (4.81)	0.122*** (7.88)	0.086*** (4.23)	0.134*** (6.96)	0.129*** (8.11)
REC	0.179*** (8.29)	0.201*** (8.99)	0.125*** (5.90)	0.227*** (8.63)	0.177*** (8.17)	0.274*** (8.81)	0.225*** (8.86)
URB	-0.029*** (-7.66)	-0.034*** (-9.15)	-0.026*** (-2.79)	-0.001*** (-4.19)	-0.008*** (-2.82)	-0.003*** (-5.63)	-0.001*** (-3.67)
CE_PI	0.152*** (7.08)						
CE_GV		-0.056*** (-4.77)					
lnCE_PE			-0.048*** (-3.03)				
CE_PAI				-0.044*** (-3.14)			
lnCE_CF					0.144*** (2.20)		
lnCE_GG						0.208*** (4.70)	
CE_MD							-0.001*** (-2.28)

_cons	1.594*** (6.84)	1.220*** (5.14)	1.175** (2.46)	0.498 (1.43)	1.255*** (4.15)	-0.250 (-0.57)	0.839*** (2.93)
N	297	297	297	297	297	297	297

Source: Authors' synthesis by Stata.

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 20 variables used in this study include: Waste Electrical and Electronic Equipment (WEEE), Private investment related to circular economy sector (CE_PI), Gross value added related to circular economy sector (CE_GV), Persons employed in circular economy sectors (CE_PE), Patents related to recycling and secondary raw materials (CE_PA), Consumption footprint (CE_CF), Greenhouse gas emissions from production activities (CE_GG), Material import dependency (CE_MD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

Table 4.19 and 4.20 shows the varying effect results from the feasible generalized least squares (FGLS) models and the panel-corrected standard errors (PCSE) indicating the strong and consistent impact of the circular economy index (CEI) on the amount of electronic waste. The regression coefficients of each component variable of the CEI all have the same sign and a statistical significance level of 1%. This result emphasizes that the development of a circular economy promotes the reduction of electronic waste. By applying the principles of a circular economy, products and resources are used more efficiently, thereby reducing the amount of electronic waste. When old electronic products are not immediately discarded but are instead collected and recycled, the components can be reused in new products, reducing the demand for new device production. This not only helps reduce electronic waste but also minimizes the exploitation of natural resources.

(ii). Robustness check of non-linear effects using CEI_CCC

Table 4.21. Robustness check of non-linear effects using CEI_CCC

	(1) WEEE	**(2) WEEE**
CEI_CCC	-0.0150*** (-6.47)	-0.0223*** (-3.97)
CEI_CCCii	0.00673*** (13.60)	0.00872*** (6.01)
FD	-0.572***	-0.671***

	(-16.33)	(-9.33)
GDP	0.147*** (13.02)	0.180*** (6.83)
PDS	0.0795*** (7.50)	0.120*** (5.89)
REC	0.193*** (12.44)	0.253*** (7.38)
URB	-0.00293*** (-8.32)	-0.00251*** (-4.80)
_cons	1.296*** (7.08)	0.606 (1.55)
N	297	297

Source: Authors' synthesis by Stata.

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_CCC), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

Table 4.21 shows the non-linear effect results from the Feasible Generalized Least Squares (FGLS) models and the Panel-Corrected Standard Errors (PCSE) indicating the strong and consistent impact of the Circular Economy Index (CEI) on the amount of electronic waste. The regression coefficients of CEI_CCCii all have the same positive correlation and the same statistical significance level of 1%. This result emphasizes that the development of a circular economy, when reaching a certain threshold, can have a negative impact on the amount of electronic waste. When the circular economy develops strongly, recycled and reused products become more accessible and cheaper. This can create a consumer stimulation effect, as consumers easily access recycled products at lower prices, thereby increasing overall consumption. The increase in consumption will lead to an increase in electronic waste as old products are replaced by new ones, even if they can be recycled.

(iii). Robustness check of synergy effects using CEI_CCC

Table 4.22. Robustness check of synergy effects using CEI_CCC

	(1) WEEE	(2) WEEE
CEI_CCC	-0.0365*** (-5.41)	-0.0371** (-2.15)
CEI_CCC_FD	0.0607*** (5.39)	0.0602** (2.44)
FD	-0.567*** (-13.44)	-0.627*** (-10.42)
GDP	0.144*** (15.79)	0.155*** (7.38)
PDS	0.102*** (11.67)	0.109*** (6.53)
REC	0.216*** (27.56)	0.228*** (8.70)
URB	-0.00226*** (-8.92)	-0.00213*** (-4.89)
_cons	1.135*** (9.92)	0.981*** (3.30)
N	297	297

Source: Authors' synthesis by Stata.

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_CCC), interaction between circular economy and financial development (CEI_CCC_FD), Financial Development (FD), Economic growth (GDP), Population density (PDS), Renewable energy consumption (REC), Urbanization (URB).*

Table 4.22 shows the results of the nonlinear effects from the Generalized Least Squares (FGLS) and Panel-Corrected Standard Errors (PCSE) models, indicating the strong and consistent impact of the interaction between the Circular Economy Index (CEI) and the Financial Development Index (FD) on the amount of electronic waste. The regression coefficients of CEI_AAA_FD all have a positive correlation and the same level of statistical significance at 1%. This result highlights the correlation between the circular economy and financial development, to a certain threshold, which will increase the amount of electronic waste. When financial development and the circular economy exceed this threshold, they can stimulate excessive consumption and production, thereby increasing the amount of electronic waste instead of reducing it. This shows the necessity of having effective management policies to regulate the development of both factors, ensuring that the goal of reducing electronic waste is maintained in the long term.

(iv). Robustness check of bidirectional and unidirectional effects using CEI_CCC

Table 4.23. Robustness check of Granger Causality Test with CEI_CCC

Table 4.23. Robustness check of Granger Causality Test with CEI_CCC

No.	Variable	W-bar	Z-bar	P-value (Z-bar)	Causality Decision
1.	**CEI_CCC → WEEE**	2.0949	4.0230	0.0001	CEI_CCC → weee_raw
	WEEE → CEI_CCC	1.0232	0.0854	0.9319	
2.	**CEI_CCC_FD → WEEE**	1.8750	3.2151	0.0013	CEI_CCC_FD → weee_raw
	WEEE → CEI_CCC_FD	1.0907	0.3331	0.7391	
3.	**WEEE → CEI_CCCii**	1.8474	3.1137	0.0018	CEI_CCCii → weee_raw
	CEI_CCCii → WEEE	0.9004	-0.3660	0.7144	

Source: Authors' synthesis by Stata.

*Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors are in parentheses. There are 6 variables used in this study include: Circular economy (CEI_CCC), interaction between circular economy and financial development (CEI_CCC_FD).*

Table 4.23 presents the results of the Granger causality test, showing a bidirectional causal relationship from CEI_CCC, CEI_CCC_FD, and CEI_CCC_FD to WEEE, indicating consistent results between the use of two models: Feasible Generalized Least Squares (FGLS) and Panel-Corrected Standard Errors (PCSE). This shows that the circular economy not only affects the amount of electronic waste, but electronic waste also impacts the circular economy. The results show similar patterns in the variables CEI_CCC_FD and CEI_CCCii concerning WEEE. This emphasizes that electronic waste management policies cannot be separated from the circular economy development strategy, but need to be integrated to optimize recycling, reuse, and minimize the negative impacts of WEEE. At the same time, funding for circular economy projects can help improve the efficiency of recycling and electronic waste management, thereby impacting the sustainable development of the economy. However, the results also emphasize that financial flows need to be allocated wisely to avoid economic growth leading to an increase in WEEE, instead focusing on solutions that optimize the value chain of electronic waste.