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THEORETICAL FRAMEWORK OF MODELING THE SYSTEMIC IMPACT OF CIRCULAR ECONOMY DEVELOPMENT ON ECONOMIC SECURITY

This article presents a theoretical framework for modeling the systemic impact of circular economy development on economic security. The proposed mathematical model is built using composite indicators derived through normalization and Principal Component Analysis (PCA) and is further expanded with time-series econometric techniques such as Vector Autoregression (VAR), Vector Error Correction Models (VECM), and Granger causality analysis. Model provides a structured analytical basis for understanding complex interdependencies and offers practical value for guiding policy development in recovery and sustainability contexts.

Keywords: *circular economy; economic security; systems analysis; extrapolation modeling; scenario analysis; time-series econometrics.*

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ТЕОРЕТИЧНІ ЗАСАДИ МОДЕЛЮВАННЯ СИСТЕМНОГО ВПЛИВУ РОЗВИТКУ ЦИРКУЛЯРНОЇ ЕКОНОМІКИ НА ЕКОНОМІЧНУ БЕЗПЕКУ

Стаття представляє теоретичну основу для моделювання системного впливу розвитку циркулярної економіки на економічну безпеку. Запропонована математична модель побудована з використанням композитних індикаторів, отриманих шляхом нормалізації та аналізу головних компонент (PCA), і додатково розширена часовими економетричними методами, такими як векторна авторегресія (VAR), векторна модель корекції помилки (VECM) та аналіз причинності Грейнджера. Модель забезпечує структуровану аналітичну базу для розуміння складних взаємозв’язків і має практичну цінність для спрямування розробки політик у контекстах відновлення та сталого розвитку.

Ключові слова: *циркулярна економіка; економічна безпека; системний аналіз; екстраполяційне моделювання; сценарний аналіз; економетрика часових рядів.*

Problem statement. The ongoing war in Ukraine has exposed critical vulnerabilities in national economic systems, underscoring the need for adaptive, resilient, and forward-looking economic strategies. In this context, ensuring economic security is not merely a theoretical concern but a practical imperative for national survival, recovery, and sustainable development. Ukraine’s ability to withstand and recover from external shocks depends increasingly on the robustness of its internal systems – financial, energy, social, environmental, and technological.

At the same time, the global policy and research landscape is experiencing a paradigmatic shift toward circular economy (CE) strategies. The CE framework has gained momentum across the European Union [1] as a means of achieving sustainability, resource independence, and long-term competitiveness. However, in develop-

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ing economies, including Ukraine, the implementation and evaluation of CE practices remain underdeveloped. There is a notable gap in measuring circularity, modeling its system-wide impacts, and integrating it meaningfully into national development strategies. CE policies in the region are often fragmented, lacking both an evidence-based foundation and a systemic analytical framework.

This study addresses this gap by offering an original systemic model that links CE development to the structural components of economic security. Grounded in the methodological principles of economic systems analysis, the research treats the national economy as a complex, interdependent system, where changes in one subsystem can propagate across others. By framing CE as both a driver and stabilizer of systemic performance, the model contributes to a deeper understanding of long-run national resilience.

Moreover, the study introduces a novel extrapolation-based methodology that allows for the transfer of empirical relationships from CE-leading countries to Ukraine. This method enables scenario-based analysis of “what-if” outcomes – projecting how Ukraine’s economic security indicators might respond if circular economy policies similar to those of advanced economies were implemented domestically. This feature transforms the model from an academic tool into a practical instrument for strategic planning and policy design, particularly in post-conflict recovery.

By combining theoretical depth, empirical modeling, and applied foresight, the research supports the broader agenda of sustainable transformation and institutional modernization in Ukraine. It also contributes methodologically to the evolving field of economic systems analysis by introducing cross-dimensional integration, dynamic modeling, and forward-looking scenario extrapolation.

Formulating the purposes of the article. The purpose of this article is to develop a systems-based econometric model that quantifies the impact of circular economy development on the structural components of economic security and to apply this model to Ukraine through scenario-based extrapolation.

Section 1. Economic Security, Circular Economy, and the indicator-based analytical framework

This section establishes the theoretical and methodological foundation for the study. It introduces the core concepts of economic security and the circular economy, outlining their systemic relevance and mutual interdependence. By framing these domains as analytically compatible, the section motivates their integration into a unified model. Particular attention is given to the selection and structuring of indicators that allow for the quantification of each dimension. The indicator framework serves as the empirical basis for constructing composite indices and exploring causal relationships through econometric modeling in subsequent sections.

The Circular Economy: conceptual foundations and strategic relevance. The circular economy (CE) is a transformative economic paradigm that seeks to decouple economic growth from resource consumption and environmental degradation [2]. In contrast to the traditional linear model of production and consumption, characterized by the "take–make–dispose" sequence, the circular economy emphasizes the continuous circulation of materials and energy through strategies such as reuse, repair, recycling, remanufacturing, and sustainable design. This paradigm promotes systemic efficiency, minimizes waste, and preserves the functional value of products and resources across economic cycles.

At its core, the CE is built upon three foundational principles: designing out waste and pollution by rethinking product life cycles and industrial processes; keeping products and materials in use through enhanced durability, maintenance, and reuse; regenerating natural systems by returning nutrients to ecosystems and reducing environmental burdens. The transition to a circular economy is not only an ecological imperative but also a strategic response to rising global uncertainties, including supply chain disruptions, resource scarcity, climate risks, and geopolitical instabilities. By optimizing material flows and enhancing resource independence, CE contributes directly to national economic resilience – making it an essential component of modern economic security strategies.

From a systemic standpoint, the circular economy touches multiple domains that overlap with economic security, including: energy transformation, through energy efficiency and the integration of renewables in production loops; technological innovation, as CE implementation drives demand for new design principles, industrial processes, and digital traceability systems; financial sustainability, by creating cost savings through efficiency gains and new business models; social resilience, via job creation in repair, recycling, and secondary materials industries; environmental protection, by reducing emissions, pollution, and ecosystem stress.

Given these broad interactions, the circular economy can be conceptualized not only as a sustainability agenda but also as a strategic lever for enhancing a country's long-term economic stability, autonomy, and adaptability. As such, it becomes analytically relevant to incorporate CE performance into the framework of economic security.

Economic Security: structural dimensions and systemic importance. Economic security (ES) refers to the capacity of a country to ensure stable, sustainable, and resilient economic development that protects national interests, maintains socio-economic stability, and mitigates internal and external risks [3]. It encompasses the economy's ability to withstand shocks, adapt to changing global conditions, and maintain critical economic functions under uncertainty. Economic security is a multidimensional concept that integrates financial, energy, innovation, environmental, and social dimensions, each contributing to the systemic stability and strategic autonomy of the national economy. To effectively analyze and assess economic security, it is necessary to disaggregate it into distinct functional components. This decomposition allows for a more precise understanding of the structure and dynamics of economic resilience. Each component – financial stability (F), energy security (P), innovative potential (I), environmental security (E), and social welfare (S) – represents a critical subsystem that contributes to the overall robustness and sustainability of the economy. Isolating these elements enables targeted analysis, facilitates data-driven policy design, and provides a clearer picture of how individual sectors respond to internal pressures and external disruptions. Moreover, this approach allows for the quantification of interdependencies between domains, which is particularly important in complex systems such as national economies.

Financial stability (F) refers to the resilience of the financial system to internal and external shocks, and its ability to maintain the normal functioning of markets, financial institutions, and monetary mechanisms. It encompasses exchange rate stability, low inflation, a balanced state budget, the stability of the banking system, a low level of debt burden, and a well-structured financial market system.

Energy security (P) reflects a country's ability to ensure a stable and reliable supply of energy resources for its economy and population. This includes the diversification of energy supply sources, availability of strategic energy reserves, energy efficiency and conservation, resilience of energy infrastructure to accidents and natural disasters, and the presence of domestic energy resources such as oil, gas, coal, and renewables.

Innovative potential (I) describes the economy's capacity to develop and implement new technologies, products, and services, contributing to long-term economic growth. This includes investment in research and development (R&D), patent activity, the level of education and workforce training, cooperation between research institutions and businesses, and support for startups and innovative enterprises.

Environmental safety (E) refers to the state's ability to maintain a healthy environment and minimize the negative impact of economic activity on nature. It includes the condition of air, water, and soil, biodiversity preservation, waste management, use of renewable resources, and implementation of environmental protection measures and education.

Social welfare (S) reflects the overall quality of life of the population, encompassing economic, social, and cultural dimensions. It includes income levels, access to education and healthcare, employment levels and working conditions, the social security system, and the quality of housing and infrastructure.

Indicators and data sources: measuring circularity and economic security. The operationalization of both economic security and the circular economy requires the use of robust, multi-dimensional indicators drawn from credible international and national data sources. Given the systemic nature of these domains, the indicators must capture diverse functional aspects across environmental, economic, social, technological, and institutional dimensions.

For each component of economic security, internationally recognized data sources provide relevant time-series indicators that ensure comparability and methodological rigor. Financial stability is measured using the Bertelsmann Transformation Index (BTI) [4], which evaluates the soundness of fiscal policy, inflation control, and currency stability. Energy security is assessed through the World Energy Council's Energy Trilemma Index [5], covering the reliability of supply, energy access, and environmental sustainability, as well as data from the IEA Energy Statistics Browser [6], which offers information on primary energy sources, energy dependency, and national energy mixes. Innovation potential is captured by the Global Innovation Index (GII) developed by WIPO [7], which reflects both innovation inputs, such as institutional capacity, human capital, R&D investment and outputs like patents and high-tech exports. Environmental safety is represented by indicators from the Yale Environmental Performance Index (EPI) [8], including lead exposure, air quality, waste management, and biodiversity metrics, complemented by Eurostat's data on air emissions, material footprint, and resource productivity. Social welfare is measured using the Human Development Index (HDI) from the UNDP [9], which combines life expectancy, education, and income dimensions, as well as OECD social indicators that reflect income inequality, employment conditions, and access to essential public services such as healthcare and education.

The measurement of circular economy progress also relies on international datasets, with Eurostat providing one of the most comprehensive and methodologically coherent statistical frameworks in this domain [10]. Core dimensions of circularity include the Circular Material Use Rate, which reflects the proportion of total material input sourced from recycled materials, and Material Import Dependency, indicating the extent to which domestic material use relies on imports. Additional metrics include the Recycling Rate of Municipal Waste, the Generation of Waste per Capita, and the Landfilling Rate of Waste, as well as sector-specific indicators such as Waste Generation by Economic Activity. Broader systemic measures include Green Public Procurement Rates, the Eco-Innovation Index as compiled by the European Environment Agency [11] and the OECD [12], Employment in Circular Economy Sectors, and levels of Private Investment in CE-related Innovation. These indicators are primarily sourced from the Eurostat Circular Economy Indicators database, the OECD Circular Economy Monitoring Framework, the Ellen MacArthur Foundation, and regional baseline reports on circularity [13].

Together, these indicators allow for the development of a composite circular economy index that reflects a country's overall performance and trajectory in transitioning from a linear to a circular model. These CE indicators are then used to examine their relationship with economic security components in the econometric framework presented in the study.

Section 2. Model construction and theoretical framework

This section outlines the construction of the analytical model used to explore the relationship between circular economy development and economic security. It begins with the formulation of a composite indicator for economic security, which integrates multiple dimensions of the concept into a single metric using normalization and weight assignment via Principal Component Analysis (PCA). A similar composite index is constructed for the circular economy. These indicators serve as the foundation for a series of regression models designed to quantify the influence of circular economy performance on economic security. The section concludes with both a baseline regression and a system of component-specific equations, which together form the structural core of the theoretical model.

Composite economic security indicator. To enable a structured and quantitative assessment of economic security, it is useful to construct a composite indicator that integrates the key components into a single synthetic measure. A composite indicator provides a consolidated view of economic resilience by aggregating multiple, potentially heterogeneous indicators into one index [14]. This approach facilitates cross-country comparisons, trend analysis over time, and quantitative modeling of systemic interactions. It also helps to reduce complexity while preserving essential information about the structure and state of the economy.

The composite economic security indicator is calculated using the following formula:

$$ES = \sum_{i=1}^{n} w_i \cdot x_i \tag{1}$$

where ES is the composite economic security indicator, x_i is the normalized value of the i-th indicator, w_i is the weight assigned to the i-th indicator, reflecting its relative importance and n is the total number of indicators included in the composite index.

Min–max normalization. To ensure proper aggregation, each indicator must be brought to a common scale, typically through normalization. One of the most widely used methods is min–max normalization, which transforms the original value of an indicator into a value between 0 and 1. The normalized value x_i of indicator y_i is calculated as follows:

$$x_i = \frac{y_i - y_{i,min}}{y_{i,max} - y_{i,min}} \tag{2}$$

where $y_{i\ ,min}$ and $y_{i,\ max}$ represent the minimum and maximum values of the indicator within the observed sample, respectively.

If the indicator has a negative effect on the overall system (i.e., higher values indicate a worsening situation), the normalized value is adjusted using the following formula:

$$x_i = 1 - \frac{y_i - y_{i,min}}{y_{i,max} - y_{i,min}} \tag{3}$$

This approach ensures that all indicators contribute to the composite index in a consistent and interpretable manner, with higher normalized values indicating more favorable outcomes.

Determining Weights via Principal Component Analysis (PCA). To assign appropriate weights w_i to individual indicators in a composite index, one widely accepted statistical method is Principal Component Analysis (PCA) [15]. PCA is a dimensionality-reduction technique that identifies the most significant variables by analyzing their variance and intercorrelations. In the context of composite indicator construction, PCA helps determine the contribution of each indicator based on its statistical influence within the dataset.

To begin, each indicator must be standardized to ensure comparability. The standardized value z_i of indicator x_i is calculated as:

$$z_i = \frac{x_i - \mu_i}{\sigma_i} \tag{4}$$

where μ_i is the mean and σ_i is the standard deviation of the indicator.

Next, either a covariance or a correlation matrix is computed. If the indicators are measured on different scales, a correlation matrix is used to capture the strength of linear relationships between variables. If all indicators are already standardized or expressed in the same units, a covariance matrix may be used. From the selected matrix, eigenvalues ($\lambda_1, \lambda_2, ..., \lambda_n$) that reflects the amount of variance explained by a principal component and corresponding eigenvectors ($v_1, v_2, ..., v_n$) that defines the direction and composition of the principal component as a linear combination of the original indicators are calculated.

The first principal component (PC_1) is selected, as it explains the highest proportion of variance in the data. It can be expressed as a linear combination of the standardized indicators:

$$PC_1 = a_1 z_1 + a_2 z_2 + \cdots + a_n z_n \tag{5}$$

where the coefficients a_i are derived from the eigenvector corresponding to PC_1 and reflect the statistical importance of each indicator.

The weights for the composite indicator are derived by normalizing the absolute values of the coefficients of the first eigenvector:

$$w_i = \frac{|a_i|}{\sum_i^n |a_j|} \tag{6}$$

This formula ensures that the weights reflect the relative contribution of each indicator to the overall variation captured by the first principal component.

Composite circular economy indicator. In a similar manner to the construction of the economic security indicator and based on equations (1)–(6), the circular economy indicator *CE* is defined as a composite index that aggregates several relevant sub-indicators reflecting key dimensions of circularity. This approach enables a holistic and quantifiable representation of a country's progress toward implementing circular economy principles. The indicator is calculated as follows:

$$CE = \sum_{i=1}^{n} w_i \cdot x_i \tag{7}$$

where *CE* is the composite circular economy indicator, x_i is the normalized value of the *i*-th sub-indicator, w_i is the weight assigned to the *i*-th sub-indicator and *n* is the total number of sub-indicators included in the composite index.

The selection of sub-indicators should reflect various dimensions of the circular economy, including resource efficiency, material reuse, recycling rates, waste generation, and dependency on imported materials. The weights w_i can be derived using the PCA-based approach described earlier to reflect the relative contribution of each sub-indicator to the overall variance in the dataset.

Base regression model. To empirically capture the relationship between the circular economy and economic security, a baseline linear regression model is introduced. This model reflects the hypothesis that the development of circular economy practices contributes to strengthening specific dimensions of economic security. The goal is to quantify the extent to which variation in the composite circular economy indicator explains changes in the respective components of economic security. The model is specified as follows:

$$ES_t = Base_0 + Eff_1 CE_t + Err_t \tag{8}$$

where ES_t denotes the value of a selected component of economic security in year *t*, CE_t is the value of the composite circular economy indicator in year *t*, $Base_0$ is the baseline level of economic security when the circular economy index is zero (intercept term), Eff_1 represents the estimated effect of the circular economy indicator on economic security (regression coefficient) and Err_t is the unexplained variation or error term for year *t*.

This basic model serves as the analytical foundation for assessing whether increases in circular economy performance are associated with improvements in economic security outcomes. It also forms the basis for more complex time-series analyses, where dynamic interdependencies and delayed effects may be explored through advanced econometric techniques.

System of component-specific regression equations. To capture the differentiated influence of the circular economy on each individual component of economic security, the baseline model can be expanded into a system of regression equations. Each equation isolates a particular domain of economic security – financial stability (*F*), energy security (*P*), innovative potential (*I*), environmental security (*E*), and social welfare (*S*) – and estimates its relationship with the circular economy indicator:

$$\begin{cases} F_t = Base_0^F + Eff_1^F CE_t^F + Err_t^F \\ P_t = Base_0^P + Eff_1^P CE_t^P + Err_t^P \\ I_t = Base_0^I + Eff_1^I CE_t^I + Err_t^I \\ E_t = Base_0^E + Eff_1^E CE_t^E + Err_t^E \\ S_t = Base_0^S + Eff_1^S CE_t^S + Err_t^S \end{cases} \tag{9}$$

where F_t, P_t, I_t, E_t, S_t denote the values of the five components of economic security in year *t*, CE_t^F, ..., CE_t^S represent the relevant (or disaggregated) circular economy indicators used to explain each component (if the same *CE* index is used across all, this can be simplified), $Base_0{}^X$ is the intercept for component *X*, $Eff_1{}^X$ is the estimated effect of the circular economy on component *X*, Err_t^X is the error term for component *X*, with $X \in \{F, P, I, E, S\}$.

This system allows for the possibility that the circular economy exerts varying degrees of influence across different aspects of economic security, depending on the structure of the economy, policy implementation, and other contextual factors.

Section 3. Methodological framework for model validation

Validation is a critical component of system modeling, particularly when the goal is to understand and quantify the influence of one subsystem (in this case, the circular economy) on another (economic security). Without empirical validation, even a well-structured theoretical model remains speculative. Applying appropriate statistical methods not only ensures the internal consistency of the model but also provides evidence that the observed relationships are statistically significant, robust over time, and not the result of random fluctuations or spurious correlations. In the context of systems analysis, such validation helps to confirm whether the modeled interconnections reflect real-world systemic behavior.

To verify the hypothesized relationship between the circular economy and economic security within a dynamic systems context, a set of time-series econometric techniques may be employed. While the present study focuses on the theoretical construction of the model, this section outlines a methodological pathway for future empirical validation. The proposed methods are rooted in systems analysis and enable the assessment of both short-term predictive relationships and long-term structural dependencies between the variables.

Stationarity assessment: Augmented Dickey–Fuller (ADF) test. In time series analysis, stationarity refers to the property whereby a variable's statistical characteristics –such as mean, variance, and autocorrelation – remain constant over time. Many econometric models, including linear regression, assume that the input data are stationary. If the data are non-stationary, the resulting estimates may be biased or misleading, potentially revealing false correlations (known as spurious regressions) and leading to inaccurate predictions.

The Augmented Dickey–Fuller (ADF) test is commonly used to verify whether a time series exhibits stationarity [16]. The null hypothesis (H_0) of the test is that the series has a unit root, i.e., it is non-stationary. The alternative hypothesis (H_1) is that the series is stationary. In the context of the base model (8) he ADF test is proposed for checking the stationarity of each time series used in the model, such as ES_t and CE_t. For instance, to assess whether economic security (ES) is stationary, the following form is applied:

$$\Delta ES_t = \alpha + \beta t + \gamma ES_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta ES_{t-i} + \varepsilon_t \tag{10}$$

where ΔES_t is the value of the time series at time t, $\Delta ES_t = ES_t - ES_{t-1}$ is the first difference, α is a constant (intercept), β_t is an optional time trend, γ is the coefficient tested for stationarity (if $\gamma < 0$, the series is considered stationary), δ_i are coefficients of lagged differences, ε_t is the random error term, p is the number of lags included to control for autocorrelation.

If either variable is found to be non-stationary, it can be transformed using first differences (e.g., $\Delta ES_t = ES_t - ES_{t-1}$) and tested again. This process is repeated until stationarity is achieved.

A similar procedure would be followed for CE_t:

$$\Delta CE_t = \alpha + \beta t + \gamma CE_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta CE_{t-i} + \varepsilon_t \tag{11}$$

Once both time series ES_t and CE_t are confirmed to be stationary (or have been properly transformed to stationarity), reliable regression estimates can be obtained and interpreted. We considered variables ES_t and CE_t to be integrated of order zero, or I(0), if they are stationary in their original form. In that case we can estimate the regression using Ordinary Least Squares (OLS) method. If a variable becomes stationary after first differencing, it is classified as order one, or $I(1)$. If stationarity is achieved only after second differencing, the series is considered $I(2)$, which is rare and typically unsuitable for standard cointegration analysis. In $I(1)$ case, ES_t and CE_t cannot be reliably analyzed using simple regression techniques in levels due to the risk of spurious results. However, if both variables are found to be $I(1)$ and not $I(2)$, it becomes methodologically valid to proceed with cointegration testing using Johansen method, which examines whether a stable long-term equilibrium relationship exists between them.

Ordinary Least Squares (OLS) approach. If the ADF test confirms that both ES_t and CE_t are stationary, i.e., integrated of order zero $I(0)$, it is methodologically appropriate to estimate the base model (8) using the Ordinary Least Squares (OLS) method [17]:

$$\hat{\beta} = (X'X) - 1X'Y \tag{12}$$

where X is the matrix of explanatory variables (including CE_t), Y is the vector of observed values of the dependent variable ES_t, β is the vector of estimated coefficients.

OLS minimizes the sum of squared residuals $\sum Err_t^2$ and produces efficient and unbiased parameter estimates under standard assumptions.

To evaluate whether the circular economy indicator has a statistically significant impact on economic security, a t-test can be performed for the coefficient Eff_1. The null hypothesis is: $H_0{:}Eff_1 = 0$ (no effect), $H_1{:}Eff_1 \neq 0$ (effect exists). The t-statistic is calculated as:

$$t = \frac{\widehat{Eff_1}}{SE\left(\widehat{Eff_1}\right)} \tag{13}$$

where $SE(Eff_1)$) is the standard error of the coefficient estimate.

If the p-value is less than 0.05, the null hypothesis is rejected, indicating that the circular economy has a statistically significant effect on economic security.

Cointegration analysis: Johansen test. When two or more time series are non-stationary, traditional regression techniques may lead to spurious results. However, if the variables are cointegrated – meaning they share a stable long-run equilibrium despite short-term fluctuations – valid modeling becomes possible. This concept is particularly important in systems analysis, where individual components may evolve independently in the short term but remain structurally linked over time.

The Johansen test is a widely used method for detecting such cointegration relationships [18]. Unlike simpler pairwise approaches (e.g., the Engle–Granger test), the Johansen framework can identify and test for multiple cointegrating vectors within a multivariate system. This makes it particularly suitable for analyzing the interdependent components of economic security.

In this study, once the Augmented Dickey-Fuller test confirms that both ES_t and CE_t are non-stationary but integrated of the same order $I(1)$, the Johansen test is applied to determine whether a long-run equilibrium relationship exists between them. If cointegration is present, it supports the theoretical assumption that circular economy performance and economic security co-evolve over time. His finding justifies the use of a Vector Error Correction Model (VECM) to capture both short-term dynamics and long-term adjustments.

The Johansen cointegration test begins with the estimation of a Vector Autoregressive (VAR) model in levels. In a two-variable case involving economic security ES_t and circular economy CE_t, the VAR model of order k can be expressed as:

$$Z_t = A_1 Z_{t-1} + A_2 Z_{t-2} + \cdots + A_k Z_{t-k} + \varepsilon_t \tag{14}$$

where $Z_t = \begin{bmatrix} ES_t \\ CE_t \end{bmatrix}$ is a vector of the non-stationary variables.

A_i are coefficient matrices for lagged variables, ε_t is a vector of white noise errors.

This form models the joint evolution of the system but does not distinguish between short-term dynamics and long-run relationships. Therefore, when variables are integrated of order one $I(1)$, the VAR model is not suitable for direct estimation in levels, as it may produce spurious results. Instead, the VAR model is reformulated into a Vector Error Correction Model (VECM) to enable proper testing for cointegration.

This transformation enables the explicit modeling of both short-run fluctuations and long-run equilibrium dynamics between the variables. The VECM form of the model is written as:

$$\Delta Z_t = \Pi Z_{t-1} + \sum_{i-1}^{k-1} \Gamma_i \Delta Z_{t-1} + \varepsilon_t \tag{15}$$

where ΔZ_t is the vector of first differences of the variables: $Z_t = \begin{bmatrix} \Delta ES_t \\ \Delta CE_t \end{bmatrix}$, Z_{t-1} is the lagged level vector $\begin{bmatrix} ES_{t-1} \\ CE_{t-1} \end{bmatrix}$, Π is the cointegration matrix containing long-run information, Γ_i are coefficient matrices for short-run effects, ε_t is the white noise error vector, k is the number of lags included in the system.

This structure allows the Johansen method to test for cointegration by examining the rank of the matrix Π. If the rank of Π is greater than zero but less than the number of variables, it indicates the existence of one or more stable long-run relationships among the variables. The matrix contains all information about the long-term equilibrium relationships between the variables in the system. Its rank determines the number of cointegrating vectors, which in turn indicates whether and how the variables are connected over the long run. The matrix Π is decomposed as:

$$\Pi = \alpha\beta' \tag{16}$$

where β is the cointegrating vector (or matrix): it defines the long-run equilibrium relationships (e.g., *ESt – Eff1 CEt*), α is the adjustment coefficients matrix: it captures how quickly each variable responds to deviations from the long-run equilibrium (i.e., how the system "corrects" back to balance).

The product αβ ensures that only those combinations of Z_t that are cointegrated are influencing the system over time. If the rank of Π is 0, then no cointegration exists. If the rank is 1, there is one stable long-run relationship – this is the ideal case for the two-variable system of economic security and circular economy indicators. The Johansen test uses the eigenvalues of Π to calculate the trace statistic and maximum eigenvalue statistic, which are compared to critical values to determine the number of cointegrating vectors. If cointegration is confirmed, the VECM framework becomes the appropriate modeling tool, capturing both the system's short-run adjustments and its long-run equilibrium path.

However, while cointegration confirms the existence of a long-run relationship, it does not reveal the direction or timing of influence between the variables [19]. This gap is addressed by Granger causality analysis [20], which explores whether past values of one variable help predict changes in another.

Granger causality: directional influence in dynamic systems. In the context of this study, the test assesses whether past values of the circular economy indicator CE_t contain statistically significant information for forecasting the economic security indicator ES_t, beyond what can be explained by past values of ES_t alone. The test compares two regression models – restricted and unrestricted. First model (restricted) – ES_t is regressed only on its own past values (this serves as the benchmark):

$$ES_t = \alpha_0 + \alpha_1 ES_{t-1} + \alpha_2 ES_{t-2} + \cdots + \varepsilon_t \quad (17)$$

where, α_0 is the intercept, and α_i are coefficients showing how strongly past values of economic security influence its current level.

In second model (unrestricted) lagged values of the circular economy indicator CE_t are added to see if they improve the model's ability to predict ES_t:

$$ES_t = \alpha_0 + \alpha_1 ES_{t-1} + \cdots + \beta_1 CE_{t-1} + \beta_2 CE_{t-2} + \cdots + \varepsilon_t, \quad (18)$$

where β_i are coefficients that capture the influence of past values of CE_t on current ES_t.

An F-test is used to evaluate whether the coefficients on the lagged CE_t terms (i.e., β_1, β_2, ...) are jointly significantly different from zero. Null hypothesis H_0: CE_t does not Granger-cause ES_t (i.e., all $\beta_i = 0$). Alternative hypothesis H_1: at least one $\beta \neq 0$. If these coefficients are jointly significant, it implies that circular economy developments contain predictive information about economic security, and we conclude that CE Granger-causes ES. The same procedure can be applied in the opposite direction to assess whether ES Granger-causes CE.

Although Granger causality does not imply true causation in a structural or theoretical sense, it provides valuable insight into the predictive structure of the dynamic system. This information is particularly useful for model specification, lag selection, and understanding temporal interdependencies, all of which are critical for constructing robust VAR or VECM models.

VAR modeling: when no cointegration is present. If both the circular economy indicator CEt and the economic security indicator ES_t are found to be non-stationary but become stationary after first differencing (i.e., both are $I(1)$), and the Johansen test reveals no cointegration, then the appropriate modeling framework is the Vector Autoregression (VAR) model in first differences [21]. The VAR model captures short-term dynamic interactions between the variables by expressing the change in each variable as a function of the past changes in both variables. Unlike the Vector Error Correction Model (VECM), the VAR in differences does not include any long-run equilibrium component, as cointegration is absent.

For the two-variable system in this study, the VAR model (with one lag, for simplicity) in first differences can be specified as:

$$\begin{cases} \Delta ES_t = \alpha_0 + \alpha_1 \Delta ES_{t-1} + \alpha_2 \Delta CE_{t-1} + \varepsilon_{1t} \\ \Delta CE_t = \beta_0 + \beta_1 \Delta CE_{t-1} + \beta_2 \Delta ES_{t-1} + \varepsilon_{2t} \end{cases} \quad (19)$$

where $\Delta ES_t = ES_t - ES_{t-1}$, $\Delta CE_t = CE_t - CE_{t-1}$, α_i and β_i are estimated coefficients, ε_{1t} and ε_{2t} are error terms.

Each equation describes how the current change in a variable depends on the previous changes in itself and the other variable. For example, the first equation shows whether past changes in circular economy performance have a significant short-term effect on changes in economic security. The VAR model is estimated using Ordinary Least Squares (OLS) for each equation. This estimation provides the short-run relationships, their statistical significance, and a framework for assessing how the variables interact dynamically over time. The appropriate number of lags to include is typically determined by information criteria such as AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion).

Although the VAR model does not account for long-run equilibrium, it remains a valuable tool for analysing interdependencies, feedback mechanisms, and forecasting short-term behaviour in systems where no cointegration exists.

VECM modeling: when cointegration is confirmed. When the circular economy indicator CE_t and the economic security indicator ES_t are both integrated of order one $I(1)$, and the Johansen test confirms the presence of cointegration, the appropriate modeling framework is the Vector Error Correction Model (VECM) [22]. Unlike the VAR model, which captures only short-run dynamics, the VECM integrates both short-term adjustments and long-run equilibrium relationships.

The VECM is derived by reparametrizing the VAR model in levels into a form that explicitly accounts for deviations from long-run equilibrium. For the two-variable system in this study, the VECM with one lag is specified as:

$$\begin{cases}\Delta ES_t = \alpha_1(ES_{t-1} - \theta \cdot CE_{t-1}) + \gamma_1 \Delta ES_{t-1} + \gamma_2 \Delta CE_{t-1} + \varepsilon_{1t} \\ \Delta CE_t = \beta_1(ES_{t-1} - \theta \cdot CE_{t-1}) + \delta_1 \Delta CE_{t-1} + \delta_2 \Delta ES_{t-1} + \varepsilon_{2t}\end{cases} \qquad (20)$$

where ΔES_t, ΔCE_t are the first differences, $ES_{t-1} - 0 \cdot CE_{t-1}$ is the error correction term, representing the long-run equilibrium relationship, α_1 and β_1 are adjustment coefficients, measuring how quickly the variables return to equilibrium after a shock, γ_i and δ_i are short-run dynamic coefficients, ε_{1t} and ε_{2t} are error terms.

The key feature of the VECM is the error correction term, which captures the deviation from long-run equilibrium at time t–1. The coefficients α_1 and β_1 show how each variable responds to restore equilibrium. For instance, if $\alpha_1 < 0$ and statistically significant, it indicates that when the system is out of equilibrium, ES_t will adjust in the direction needed to correct the imbalance. Estimation of the VECM provides insight into long-run relationships (via the cointegrating vector θ), speed of adjustment (via α_1 and β_1) and short-run causality and feedback loops (via the lagged differenced terms). Thus, the VECM offers a comprehensive framework that combines the strengths of both long-run equilibrium analysis and short-run dynamic modeling. In the context of circular economy and economic security, it enables the evaluation of whether improvements in circular economy performance lead to sustainable, equilibrium-consistent gains in economic security over time.

Modeling Procedure Overview. The process of selecting an appropriate modeling framework for analysing the relationship between circular economy performance and economic security follows a structured sequence of econometric tests and decisions.

The procedure begins with a stationarity check using the Augmented Dickey–Fuller test. If both variables are stationary in levels (i.e., integrated of order zero, $I(0)$), a standard regression using Ordinary Least Squares is appropriate.

If the variables are non-stationary but become stationary after first differencing (i.e., $I(1)$), the next step is to test for cointegration using the Johansen method. This involves estimating a Vector Autoregressive model in levels, reformulating it as a Vector Error Correction Model, and evaluating the rank of the cointegration matrix Π.

If cointegration is confirmed, the VECM is applied to capture both short- and long-term dynamics. If no cointegration is found, a VAR model in first differences is used to model short-term interactions only. In parallel, Granger causality tests help determine the direction of predictive influence between variables, providing valuable input for model specification. Fig. 1 illustrates the complete decision-making process.

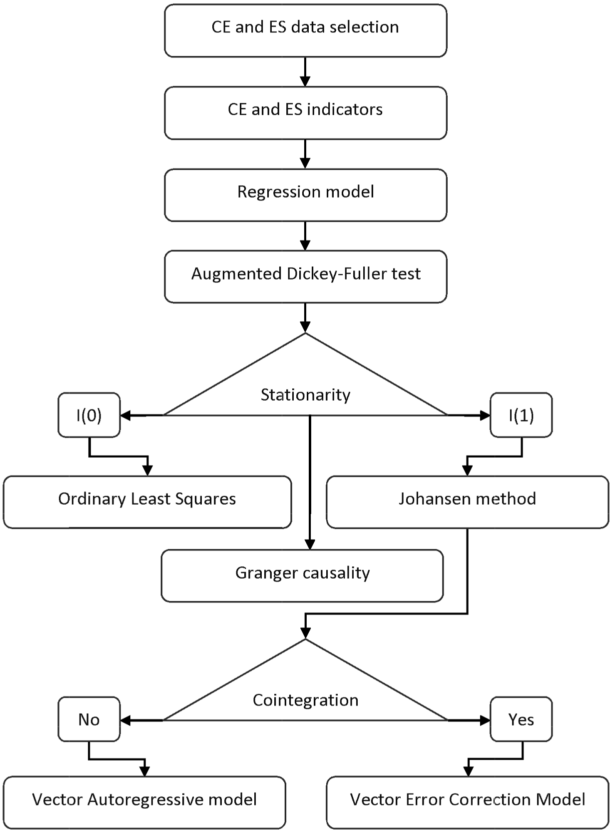

Figure 1. **Econometric modeling pathway for circular economy and economic security analysis**

Section 4. Adaptation for Ukraine and exploring future scenarios

This section proposes the adaptation of the theoretical framework to the Ukrainian context in order to assess the potential effects of circular economy reforms on national economic security. Building on the regression estimates derived from countries with more advanced circular economy practices, a "what-if" analytical approach is introduced. The aim is to simulate how Ukraine's economic security profile might respond if similar policy measures were implemented. This modeling exercise provides a basis for scenario-based evaluation of policy choices in a post-crisis development environment.

Applying regression results for Ukraine. To evaluate the potential impact of circular economy development on Ukraine's economic security, this study proposes an extrapolation approach based on the regression models previously estimated for countries that have already implemented circular economy policies. The logic follows from the base model (8) and its extended component-specific system (9). In this extrapolation, the estimated regression coefficients derived from a donor country are applied to Ukrainian data. The extrapolated values of each component of economic security for Ukraine are calculated as follows:

$$\begin{cases} \widehat{F_{UA}} = \widehat{Base_0^F} + \widehat{Eff_1^F} CE_{UA}^F \\ \widehat{P_{UA}} = \widehat{Base_0^P} + \widehat{Eff_1^P} CE_{UA}^P \\ \widehat{I_{UA}} = \widehat{Base_0^I} + \widehat{Eff_1^I} CE_{UA}^I \\ \widehat{E_{UA}} = \widehat{Base_0^E} + \widehat{Eff_1^E} CE_{UA}^E \\ \widehat{S_{UA}} = \widehat{Base_0^S} + \widehat{Eff_1^S} CE_{UA}^S \end{cases} \tag{21}$$

where X_{UA} represent the extrapolated values of Ukraine's economic security components, $Base_0^X$ and Eff_1^X are the intercept and slope coefficients transferred from the donor country model for component X, CE_{UA}^X is the hypothetical circular economy sub-index for Ukraine under an assumed policy scenario, with $X \in \{F, P, I, E, S\}$.

The error terms Err_t^X are excluded in this step because the extrapolation focuses on the expected (deterministic) component of the model. This formulation treats the system as a vector-valued approximation, enabling a multidimensional assessment of how CE policies might influence Ukraine's economic security profile.

By comparing the extrapolated scenario with actual values, this approach enables a structured "before-and-after" evaluation of circular economy impacts, offering insights into which dimensions of economic security would benefit most from reform adoption.

Before-and-after comparison. To assess the practical significance of circular economy reforms on Ukraine's economic security, a comparative analysis is conducted between two scenarios:

1. The status quo, which reflects the actual values of economic security indicators observed in Ukraine
2. The policy scenario, which reflects the extrapolated values F_{UA}, P_{UA}, I_{UA}, E_{UA}, S_{UA} obtained from equation (21), assuming Ukraine had implemented circular economy measures similar to those of the reference country.

The differences between actual and extrapolated values indicate the hypothetical gain (or loss) in each component of economic security due to circular economy integration. This comparison provides a grounded basis for evaluating not only the overall effectiveness of such reforms, but also which dimensions of economic security would benefit most. The before-and-after analysis adds a scenario-based dimension to the model, allowing for evidence-informed policy discourse on the benefits and trade-offs of circular economy strategies in a national security context.

While the extrapolation analysis provides a static snapshot of what the economic security landscape in Ukraine could look like under alternative policy scenarios, it does not capture how these effects may evolve over time. To address this limitation and assess the temporal dimension of circular economy impacts, three parallel tools are considered: ARIMA models, machine learning algorithms, and simulation-based approaches – each offering unique advantages for exploring future trajectories of economic security under varying conditions.

ARIMA modeling. The AutoRegressive Integrated Moving Average (ARIMA) model is one of the most widely used approaches for forecasting economic time series, particularly when the data exhibit strong trends, autocorrelation, or seasonality [23]. ARIMA is a univariate model, meaning it forecasts the future value of a variable based solely on its own past values and past errors, making it especially suitable when a clean, interpretable projection is needed.

An ARIMA model is typically denoted as ARIMA(*p, d, q*), where p refers to the number of autoregressive (AR) terms, which capture the influence of past values of the variable, *d* indicates the degree of differencing needed to make the series stationary, *q* specifies the number of moving average (MA) terms, which account for past forecast errors.

ES_t forecasting might be expressed as:

$$ES_t = \alpha + \sum_{i=1}^{p} \beta_i ES_{t-i} + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j} + \varepsilon_t \tag{22}$$

where ε_t represents the random error term at time *t*, b_i and γ_j are coefficients estimated from the data.

The ARIMA model is particularly advantageous due to its simplicity, transparency, and ease of interpretation – features that are especially valuable in policy-oriented contexts. However, its reliance on linear relationships and single-variable input makes it less effective in situations where economic security is influenced by multiple interacting factors, such as complex feedback loops or nonlinear patterns – areas where more advanced methods may be required.

Machine learning forecasting. While traditional statistical models like ARIMA are well-suited for structured and linear data, machine learning (ML) approaches offer greater flexibility in modeling complex, nonlinear, and multi-factor relationships that often characterize the dynamics of economic security [24]. These methods are particularly useful when the relationships between variables are not easily specified a priori or when high-dimensional input data are available.

In this context, machine learning techniques such as Long Short-Term Memory (LSTM) neural networks, gradient boosting algorithms (e.g., XGBoost, LightGBM), or ensemble regression models can be applied to forecast economic security indicators using both historical values of circular economy metrics and lagged values of the target variable itself.

A generalized ML-based forecasting structure can be expressed as:

$$ES_t = f(CE_{t-1}, ES_{t-1}, ES_{t-2}, \dots) \tag{23}$$

where $f(\cdot)$ denotes a nonlinear mapping learned from the data.

This flexible formulation allows the model to uncover hidden patterns, interaction effects, and nonlinear trajectories that may be missed by conventional approaches. Machine learning forecasting is particularly well-suited for long-run projections, where nonlinear dependencies and multi-step effects accumulate over time. These models are also highly adaptive and can improve their predictive accuracy as more data become available.

However, their key drawback lies in the lack of interpretability – especially for neural networks, which may pose challenges for policy communication and causal reasoning. As a result, ML methods are often best used in combination with transparent models to validate patterns or simulate alternative scenarios.

Scenario simulation modeling. In addition to statistical and machine learning methods, simulation-based forecasting provides a powerful tool for analyzing the future dynamics of economic systems under uncertainty and hypothetical interventions. These approaches are particularly valuable when the goal is not only to predict outcomes but also to explore a wide range of potential scenarios, structural changes, or policy shocks. Two key simulation techniques applicable in this context are Monte Carlo simulation and Agent-Based Modeling (ABM).

Monte Carlo simulation involves running a large number of stochastic experiments to assess the range and probability distribution of future outcomes [25]. In the context of this study, key variables such as future values of the circular economy indicator CE_t, or the effectiveness coefficient Eff_1, can be treated as random variables drawn from defined probability distributions. The extrapolation model (21) is then simulated repeatedly across thousands of runs to produce a distribution of possible economic security trajectories. This approach is particularly well-suited for risk assessment, sensitivity analysis, and stress testing, enabling researchers and policymakers to evaluate how changes in assumptions or external shocks may influence long-term results.

Agent-Based Modeling provides a bottom-up simulation framework in which individual economic actors, such as firms, households, or government agencies, are modeled as autonomous agents with defined behaviors, decision rules and interactions [26]. In this setup, a CE-related policy (e.g., subsidies for recycling, eco-design regulations) can be introduced at the government level, and the model tracks how this policy influences the behavior of firms and households over time. ABM is particularly useful for capturing emergent effects, feedback loops, and behavioral heterogeneity, which are difficult to represent in aggregate statistical models. This makes it an ideal tool for evaluating complex systems such as the interplay between circular economy interventions and national economic security dynamics.

Comparison of forecasting approaches. To synthesize the forecasting options presented in this section, Tab. 1 provides a comparative overview of the three methodological approaches: ARIMA, machine learning, and simulation modeling.

Table 1. **Comparison of forecasting approaches**

Method	Strengths	Limitations	Best used for
ARIMA	– Transparent, interpretable – Handles trends and autocorrelation well	– Assumes linearity – Limited to univariate inputs	Short-term forecasting with clear time-series structure
Machine learning	– Captures nonlinear and complex relationships – High predictive accuracy	– Requires more data – Often difficult to interpret ("black box")	Long-term forecasting with multifactor influences
Simulation modeling	– Handles uncertainty and behavioral diversity – Useful for scenario testing	– High complexity – Requires strong assumptions and calibration	Policy impact analysis and alternative scenario evaluation

Each approach offers distinct strengths and limitations depending on the nature of the data, the complexity of the relationships involved, and the intended use of the forecast. By contrasting these tools side by side, the table helps clarify how different modeling strategies can support evidence-based analysis of the future trajectory of economic security under circular economy reforms.

Conclusions. This study developed a theoretical modeling framework to examine how circular economy development may influence various components of economic security. Drawing from system dynamics, regression analysis, and cointegration theory, the model integrates a composite CE indicator and disaggregates ES into five key components: financial stability, energy security, innovation potential, environmental safety, and social well-being. While empirical validation remains a task for future research, the structure and logic of the model support the hypothesis that progress in circular economy performance is likely to generate positive effects on national economic security, both in the short and long term.

The proposed framework offers a structured approach for policymakers to evaluate the potential security benefits of circular economy strategies. By combining composite indicators with econometric analysis and scenario-based extrapolation, the model allows not only for evidence-based assessment but also for simulation of alternative policy outcomes – including "what-if" analyses for countries like Ukraine. This can inform the design of national CE roadmaps aligned with broader security and resilience goals.

This article presents a conceptual and theoretical model without empirical estimation. The reliability of its results therefore depends on future data availability and correct specification of real-world parameters. The framework also assumes linear relationships in its base regression form and relies on composite indices, which can obscure heterogeneity in underlying indicators. Moreover, while the system is well suited to national-level analysis, it does not yet account for regional variations or international interdependencies.

Several avenues for future investigation emerge from this study. First, empirical validation of the model using real data across multiple countries and years is essential. Second, integration of machine learning techniques or agent-based models can enhance the analysis of nonlinear and behavioral dynamics. Finally, incorporating more detailed circular economy sub-indicators, such as waste intensity, green innovation uptake, or material dependency, would enable a more granular understanding of which CE strategies are most effective in strengthening economic security.

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