DOI: 10.47743/ECO4ALL.2025.1.9

UNRAVELING CIRCULAR ECONOMY DYNAMICS IN THE EU: A BAYESIAN NETWORK ANALYSIS

ESMA NUR CINICIOGLU
Istanbul University
Istanbul, Türkiye
esmanurc@istanbul.edu.tr

Abstract
This study applies Bayesian Network (BN) modelling to assess changes in the interdependencies among key Circular economy (CE) indicators across two timeframes:2012-2016 and 2017-2021. Using data from EURUSTAT monitoring framework, we analyse how variables such as material footprint, material import dependency, and private investment in Circular Economy interact over time. Structure learning is conducted separately for each period, followed by posterior updates based on selected evidence. The results reveal a temporal shift in material sourcing. While high material consumption in the earlier period is primarily supported by domestic resources, the later period showed increased dependency on imported materials under similar conditions. Furthermore, high private investment in Circular economy does not automatically reduce material import dependency and may coincide with higher external reliance, suggesting delayed impacts or structural limitations.
Keywords: *Bayesian networks, Circular economy and Sustainability, EU Circular Economy Policy, Circular economy indicators, Material Import Dependency*
JEL Classification: Q01, Q56, Q32

1. INTRODUCTION

The depletion of natural resources, a growing population, and the alarming levels of pollution – byproducts of a linear, wasteful consumption model−have made the transition to a circular economy imperative. The world's largest economies, which are largely responsible for perpetuating this wasteful consumption model, must now lead to transition to a circular economy. Rather than stemming from altruism, this move was the direct consequence of the need of a sustainable development which is unattainable under the wasteful consumption pattern of the linear economy.

A linear economy is a traditional economic model based on a "take-make-dispose" approach where natural resources are extracted, used to produce goods and discarded as waste. Circular Economy on the other hand, is designed to minimize waste and make the most of resources by keeping products, materials, and components in use for as long as possible. The three principles called as 3Rs that the circular economy is based are reduce, reuse and recycle.

Enabling the transition from a linear to a circular economy requires significant changes in policies and regulations. As Alberich, Pansela and Hartley (2023) state, the shift toward a circular economy has become the central focus for governments, major corporations, and advocacy groups (Ekins *et al.*, 2019; Kircherr, Reike and Hekkert, 2017; Murray, Skene and Haynes, 2017). In this context, China emerged as an early leader on the global stage. In 2005, the State Council of China issued and official directive promoting the circular economy. This was followed by the enactment of the Circular Economy Promotion Law in 2015 (Zhao, 2020). On the hand, the European Union has also acknowledged that the transition to a circular economy is crucial for achieving sustainability, which has been followed by the enactment of key policy milestones, as illustrated in the timeline presented in Figure 1. To fast-track Europe's shift from a linear to a circular model European Union launched the Circular Economy Action Plan. The aim of the plan was to boost competitiveness, support economic growth and faster employment opportunities. To measure the progress towards the goals a dedicated monitoring framework was launched in 2018, focusing on five core areas: production and consumption, waste management, secondary raw materials, competitiveness and innovation, and global sustainability and resilience. These developments laid the foundation for the European Green Deal, adopted by the European Parliament in 2019 as a blueprint for sustainable growth across the EU. In line with this strategy in 2020 the Circular Economy Action plan was updated, emphasizing sustainable product design, reuse, and recycling to improve resource efficiency and minimize waste generation.

Figure 1. Major circular economy milestones relevant to the EU

Monitoring the transition toward a circular economy (CE) requires a systematic approach that captures the complex relationships between resource use, waste generation, economic activity, and sustainability outcomes. The European Commission's CE monitoring framework provides a structured dataset to evaluate progress across EU member states. This framework encompasses a wide range of indicators including material footprint, resource productivity, waste generation, recycling rates, circular material use, greenhouse gas emissions, employment, investment, patents, and GDP per capita. Understanding the interrelationships between circular economy indicators is essential for designing effective policy interventions. Indicators in a CE system are expected to be interconnected and the strength and nature of the relationships between the indicators may reflect the system's internal coherence. Addressing this need, Cinicioglu (2025) investigated the probabilistic dependency structure among CE indicators across EU countries, using data from the EUROSTAT database. The study focused on three dimensions: production and consumption, competitiveness and innovation, and global sustainability and resilience.

These analytical efforts align with broader policy goals: over the past decade, circular economy policies within the European Union have aimed to facilitate systemic transformation across multiple sectors. A critical next step is to evaluate the actual impact of these measures– specifically, whether they have driven meaningful change and to what extent they have influenced CE performance across member states. There exist various studies that questions the effectiveness of the CE practices. Georgescu *et al.* (2025) apply a multiple linear regression model with fixed effects panel data to examine the factors influencing the efficiency of the circular economy transition in the EU. Sanz-Torró (2025) uses Data Envelopment Analysis and the Sequential Malmquist Index to analyse the effectiveness of the national CE polices across EU and to identify the items of circularity that need improvement.

In this study, we follow the convention of Cinicioglu (2025) and use Bayesian networks (BNs) to explore the dependency structure of CE indicators. These indicators can be naturally interrelated due to underlying economic and material flows. However, the emergence of a stronger and more coherent dependency structure over time may signal the systemic effect of CE policies. To explore this, we learn Bayesian network structures from data provided by the EU Monitoring Framework across two time periods: 2012–2016 and 2017–2021. This comparison allows us to assess how the relationships between indicators have evolved and to infer the potential influence of CE policies on the internal coherence of the system.

The remainder of this paper is structured as follows: Section 2 outlines the Bayesian network methodology, the dataset and the CE indicators used in this study. Section 3 presents the comparative analysis of the BNs learned across different timeframes. Section 4 concludes with a discussion of the main results and key findings.

2. METHODOLOGY & DATA SET

2.1. Bayesian networks

Bayesian networks are acyclic probabilistic graphical networks where each node represents a variable and each arc represents the probabilistic dependency between the variables. In a BN if there is an arc going from a node to another, the node at the end of the arc is called the child node, and the node from which the arc originates is called the parent node. As represented in Equation (1) given below each variable in a Bayesian network (BN) possess a probability distribution given its parents and the product of these probability distributions constitute the joint probability distribution of the network.

$$P(X_1, \dots, X_N) = \prod_{i=1}^{N} P(X_i | Pa(X_i)) \quad (1)$$

A simplistic BN with three variables A, B and C is given in Figure 2. Here the variables A and B have no parent variables in the network and are therefore represented with their marginal distributions $P(A)$ and $P(B)$. Variable C, on the other hand, is the child variable of both A and B and as can be seen in the network its probability distribution $P(C|A, B)$ is conditioned on its parents.

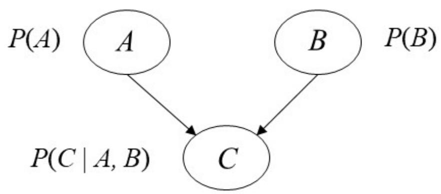

Figure 2. An illustrative Bayesian network with three variables

There exist two different layers of the BNs, one where the graphical structure is given and which represents the probabilistic dependency structure between the variables and the second are the parameters of the network which are the conditional probability distributions that the variables do possess. Both the graphical and the computational layer can be based on expert knowledge or be learned from data directly using the existing structure and parameter learning algorithms. These algorithms typically rely on statistical independence tests or on the optimization of a network scoring function

The structure of a BN can be Bayesian networks offer a probabilistic modelling framework capable of identifying dependencies among these variables and quantifying their interactions. Unlike conventional statistical techniques, BNs allow for scenario analysis and uncertainty quantification, making them particularly useful for sustainability assessments. Moreover, the ability to model non-linear relationships, the inference capability through Bayesian updating offers a flexible structure which is not limited to a single output variable. The use of BNs extends to a wide set of different areas from targeted advertising (Cinicioglu and Shenoy, 2016) to healthcare Kyrimi *et al.* (2025), competitiveness and innovation analysis (Cinicioglu, Önsel and Ülengin, 2012; Cinicioglu *et al.*, 2017) and geopolitical risk Bozcu and Cinicioglu (2023). In this work we will use BNs to analyse the changing dependency structure of the selected CE indicators obtained from the European Monitoring Framework. Both the network structure and also the parameters will be learned from data using the Bayesian search (Cooper and Herskovitz, 1992; Heckerman, 1995) and Expectation Maximization (EM) algorithm respectively. The following section describes the set of CE indicators used to learn the BNs.

2.2. Data Set

The set of indicators used to learn the BNs is derived from the EU Monitoring Framework for CE which consists of five thematic sections with a total of eleven statistical indicators capturing the key dimensions of circular economy. In this study seven different CE indicators are selected based on the availability across a 10-year period (2012-2021) and for 27 EU countries. The selected CE indicators (Eurostat, 2024 a-f) are as follows: From the Production & Consumption thematic section: Material footprint (pc020) and generation of plastic packaging waste per capita (pc050). From the competitiveness & Innovation section: two variables from cie012, gross investment in tangible goods and value added at factor costs in recycling, repair and reuse and rental & leasing. From the global sustainability and resilience thematic section: Patents related to recycling and secondary raw materials (gsr 010) and Material import dependency (gsr 030). This 10-year data set is divided in two to be analysed across the two five-year periods, 2012-2016 and 2017-2021 in order to see the effect of the EU CE policies and regulations on the dependency structure of the CE indicators. In total the data set includes 270 observations for seven CE indicators (variables), 135 for each 5-year timespan. Before the BN learning is applied on the data set, all the variables are discretized with four equal-width intervals, showing the different states of each variable. Here, though the variables are the same CE indicators, the fact that they belong to different time frames results in variations in the underlying data distributions. Consequently, the discretized intervals (states) of each variable may differ across the two time periods. These states should be interpreted as data-driven levels specific to each timeframe, reflecting the variable's behaviour within that particular period. Therefore, these states should be considered as the levels of that variable. In the following section we present and analyse the BNs learned from this discretized data sets for the two different timeframes.

3. COMPARATIVE ANALYSIS ON BAYESIAN NETWORKS

The purpose of this analysis is to examine how the dependency structure between the circular economy indicators has evolved over time. To this end, two distinct BNs are learned, each corresponding to a different five-year period. Figure 3 presents these networks: The one on the left-hand-side was learned from data covering the 2012-2016 period and the BN on the RHS is learned from the following second five-year time frame, 2017-2021. We observe that the BN belonging to the first five year is showing a denser set of arcs compared to the one on RHS learned from the time frame 2017-2021.Though this observed difference may suggest a potential shift in the interdependencies among circular economy indicators over time, one should keep in mind that a score-based algorithm is used for structure learning and an analysis based on the number and direction of arcs may be misleading. A score-based algorithm typically balances model fit with complexity and adopts to the data characteristics each time independently. Therefore, we will restrict our analysis to the changes in the marginal and conditional probabilities of the variables in the network. Notice that the marginal probabilities of the variables present in the network can directly be read from the BN given in Figure 3. Though no big differences are realized at first glance, one should keep in mind that for some of the variables the discretized intervals (states) of each variable does differ. For example, the variable "plastic packaging generations per capita" exhibits a clear upward trends over the years. In the BN corresponding to the 2012-2016 period (LHS), the highest state levels s3 and s4 correspond to value ranges of 41-54 and 54 and above, respectively. In contrast, in the 2017-2021 BN (RHS), the same states s3 and s4 cover the higher ranges of 44-59 and 59 and above, reflecting an increasing consumption over time.

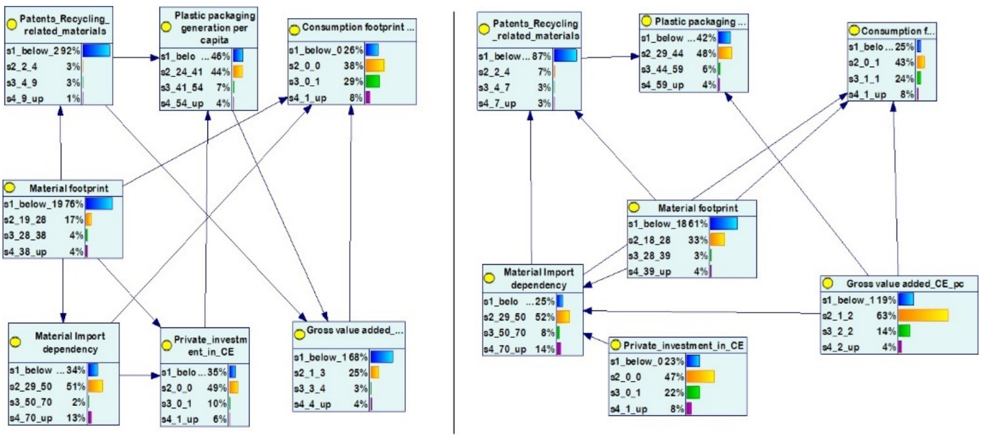

Figure 3. Structure of the Bayesian networks learned from two distinct time frames: 2012-2016 (LHS) and 2017-2021 (RHS)

In Figure 4 below we present the updated posterior probabilities of the BNs after observing the same evidence *P*(Material Footprint = s4) across the two different time frames. In the EUROSTAT Monitoring framework the variable "Material footprint" refers to the annual total raw material consumption per inhabitant. In the updated BN corresponding the time frame 2012-2016 we see that although the raw material consumption is in its highest level, the material import dependency seems to be largely unaffected. Material import dependency refers to the ratio of imports over direct material inputs. A reasonable conclusion from this result is that, during the earlier 5-year timeframe (2012-2016), the observed increase in material consumption is primarily met through domestic resource extraction. By contrast, the later 5-year timeframe (2017-2021) the same evidence leads to an increase of about 18% for the higher levels of states (s2, s3, s4) on material import dependency. This suggests a growing reliance on external resources among EU countries. This trend highlights an important concern: for many countries, rising level of material consumption are increasingly associated with external dependence, potentially generating both environmental and strategic vulnerabilities.

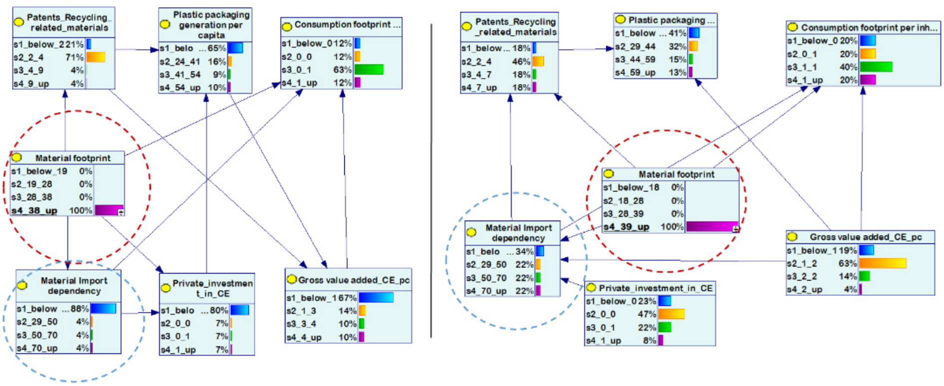

Figure 4. Updated posterior BNs for the same evidence: *P*(Material Footprint = s4) across two time frames: 2012-2016 (LHS) and 2017-2021 (RHS)

As the next step of our analysis, we observe the effect of observing the evidence for the highest level of the variable "Private investment in CE". "Private investment in CE" refers to cie012, which has its full name as "Private investment and Gross Added Value Related to Circular Economy Sectors". This indicator assesses the financial investments and value added by the private sector entities actively engaged in CE activities. It reflects the economic output of industries dedicated to sustainability, recycling and material reuse. During the first 5-year period when the highest level s4 for Private investment in CE is observed, the updated probabilities for Material Import Dependency show an upward trend. This trend becomes even more pronounced in the second five-year period, where after observing the highest level for Private Investment in CE the updated marginal probability of Material Import Dependency reaches to 46 % for its highest level of state s4. These results suggest that high investment in CE does not automatically lead to a reduction in material import dependency, particularly in short term. The following section presents the results and concludes the study.

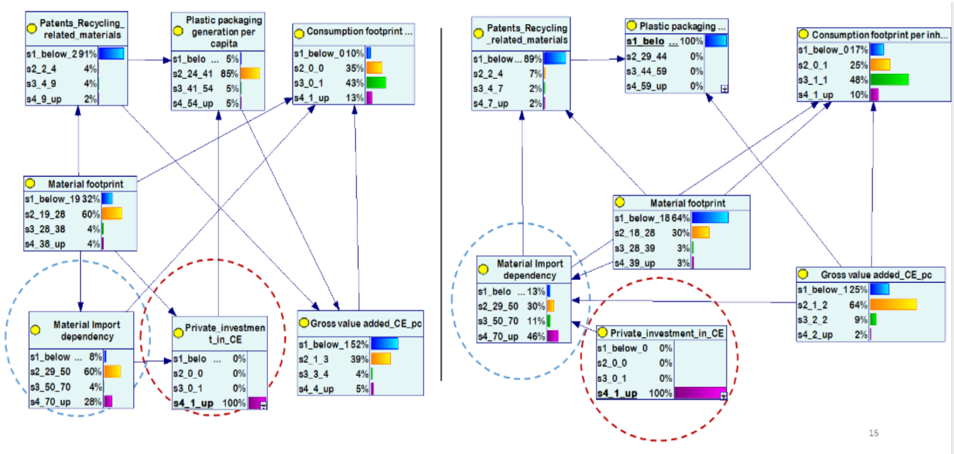

Figure 5. Updated posterior BNs for the same evidence: *P*(Private investment in CE|Material footprint & Material Import Dependency= s4) across two time frames: 2012-2016 (LHS) and 2017-2021 (RHS)

4. CONCLUSIONS

In this study we applied a Bayesian network analysis on the selected Circular Economy indicators from European monitoring framework to investigate the evolving relationships over the two consecutive five-year periods (2012-2016 and 2017-2021) in EU countries. By comparing updated posterior probabilities in response to the same evidence, we captured shifts in dependency structures over time, particularly with regard to material import dependency and investment in circular economy initiatives.

Our findings reveal that while material consumption has increased over time, its sources have shifted from primarily domestic extraction in the earlier period to greater reliance on imported resources in the later years. Additionally, we find that higher levels of private investment in CE do not automatically translate into reduced material import dependency. In fact, in the more recent timeframe, increased investment is associated with higher import dependency, suggesting a potential time lag in the impact of CE measures, possible misalignments between investment focus and material substitution goals, or inherent structural constraints within domestic economies. These insights underline the importance of aligning circular economy strategies not only with sustainability targets but also with economic resilience and material self-sufficiency. Closing the gap between investment and material outcomes will require targeted policy action and continuous monitoring using robust, data driven methods.

References

1) Alberich, J.P., Pansera, M. and Hartley, S. (2023). Understanding the EU's circular economy policies through futures of circularity. *Journal of Cleaner Production*, *385*, p. 135723.
2) Bozcu, G. and Çinicioğlu, E.N. (2023). Ulusal güvenlik karar problemlerinde karşıtsal risk analizi: Doğu Akdeniz problemi örnek modelleme. *Ardahan Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 5(1), pp. 62–73.
3) Cinicioglu, E.N. (2025). The EU's probabilistic dependency structure towards the goal of a circular economy. *Sustainable Development, Culture, Traditions Journal*, 16(a), pp. 42–52.
4) Cinicioglu, E.N. and Shenoy, P.P. (2016). A new heuristic for learning Bayesian networks from limited datasets: a real-time recommendation system application with RFID systems in grocery stores. *Annals of Operations Research*, 244, pp. 385–405.
5) Cinicioglu, E.N., Önsel, Ş. and Ülengin, F. (2012). Competitiveness analysis of automotive industry in Turkey using Bayesian networks. *Expert Systems with Applications*, 39(12), pp. 10923–10932.
6) Cooper, G.F. and Herskovits, E. (1992). A Bayesian method for the induction of probabilistic networks from data. *Machine Learning*, 9, pp. 309–347.
7) Ekins, P., Domenech Aparisi, T., Drummond, P., Bleischwitz, R., Hughes, N. and Lotti, L. (2020). *The circular economy: What, why, how and where*.
8) Eurostat (2024a). Material footprint. [online] Available at: https://ec.europa.eu/eurostat/cache/metadata/en/cei_pc020_esmsip2.htm [Accessed 1 Feb. 2025].
9) Eurostat (2024b). Generation of plastic packaging waste per capita. [online]Available at: https://ec.europa.eu/eurostat/cache/metadata/en/cei_pc050_esmsip2.htm [Accessed 1 Feb. 2025].
10) Eurostat (2024c). Private investment, jobs and gross value added related to circular economy sectors. [online] Available at: https://ec.europa.eu/eurostat/cache/metadata/en/cei_cie011_esmsip2.htm [Accessed 1 Feb. 2025].
11) Eurostat (2024d). Patents related to waste management and recycling. [online] Available at: https://ec.europa.eu/eurostat/cache/metadata/en/cei_cie020_esmsip2.htm [Accessed 1 Feb. 2025].
12) Eurostat (2024e). Consumption footprint. [online] Available at: https://ec.europa.eu/eurostat/cache/metadata/en/cei_gsr010_esmsip2.htm [Accessed 1 Feb. 2025].
13) Eurostat (2024f). Material import dependency. [online] Available at: https://ec.europa.eu/eurostat/cache/metadata/en/cei_gsr030_esmsip2.htm [Accessed 1 Feb. 2025].
14) Georgescu, L.P., Fortea, C., Antohi, V.M., Balsalobre-Lorente, D., Zlati, M.L. and Barbuta–Misu, N. (2025). Economic, technological and environmental drivers of the circular economy in the European Union: a panel data analysis. *Environmental Sciences Europe*, 37(1), pp.1–30.
15) Heckerman, D., Geiger, D. and Chickering, D.M. (1995). Learning Bayesian networks: The combination of knowledge and statistical data. *Machine Learning*, 20, pp. 197–243.

16) Kirchherr, J., Reike, D. and Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling*, 127, pp. 221–232.
17) Kyrimi, E., Mossadegh, S., Wohlgemut, J.M., Stoner, R.S., Tai, N.R. and Marsh, W. (2025). Counterfactual reasoning using causal Bayesian networks as a healthcare governance tool. *International Journal of Medical Informatics*, 193, p. 105681.
18) Murray, A., Skene, K. and Haynes, K. (2017). The circular economy: an interdisciplinary exploration of the concept and application in a global context. *Journal of Business Ethics*, 140, pp. 369–380.
19) Sanz-Torró, V., Calafat-Marzal, C., Guaita-Martinez, J.M. and Vega, V. (2025). Assessment of European countries' national circular economy policies. *Journal of Environmental Management*, 373, p. 123835.
20) Zhao, Y. (2020). China in transition towards a circular economy: from policy to practice. *Journal of Property, Planning and Environmental Law*, 12(3), pp. 187–202.