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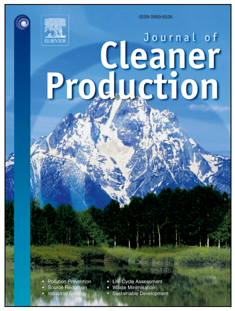

The importance of the structural pattern for the resilience of circular economy networks: A network-based approach

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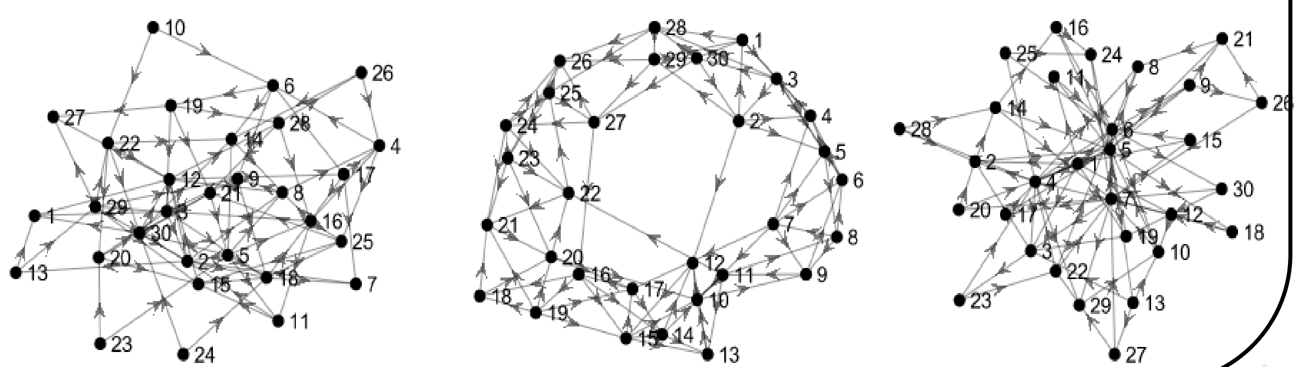
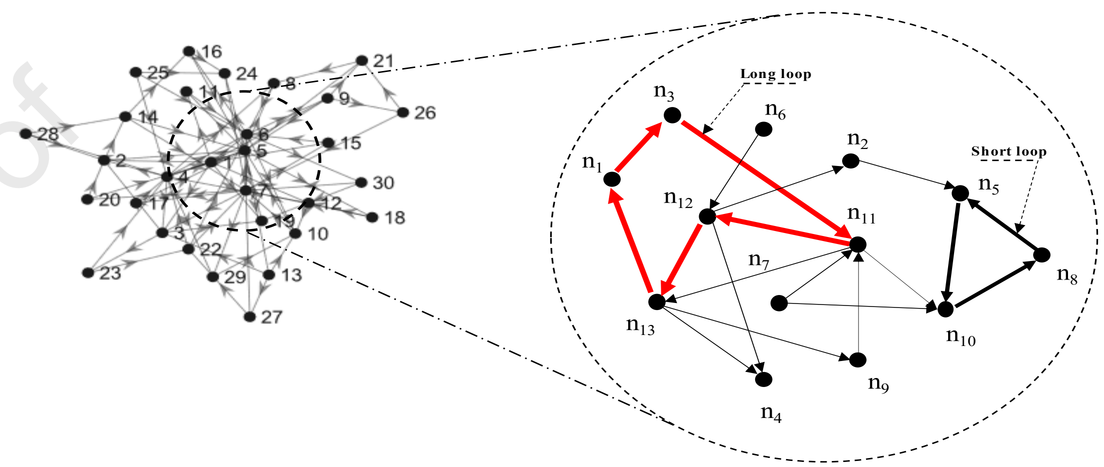
Structural Pattern

- Scale-free
- Erdos-Renyii
- Small-world



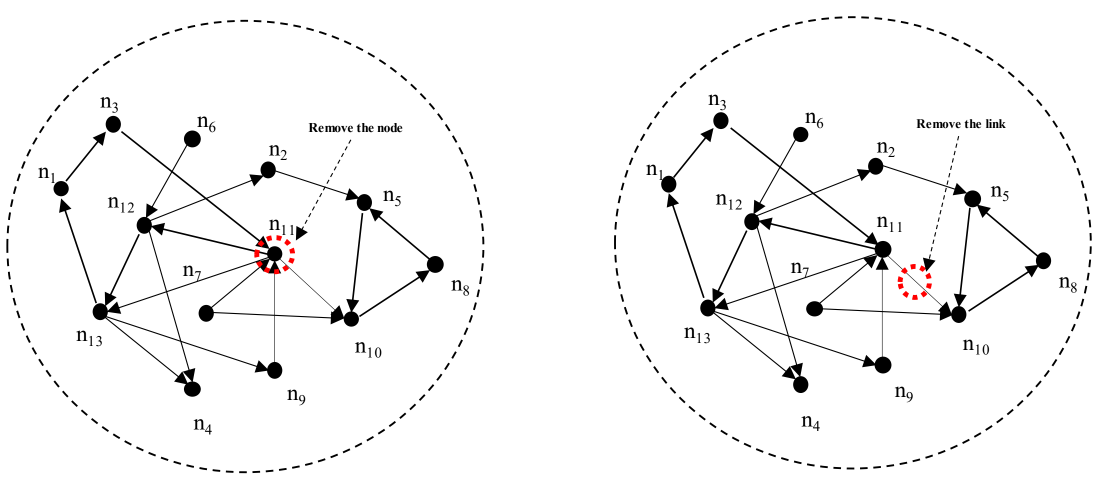
Resource Loop Structures

- Short loops (i.e. repair, remanufacture etc.)
- Long loops (i.e. recycle)

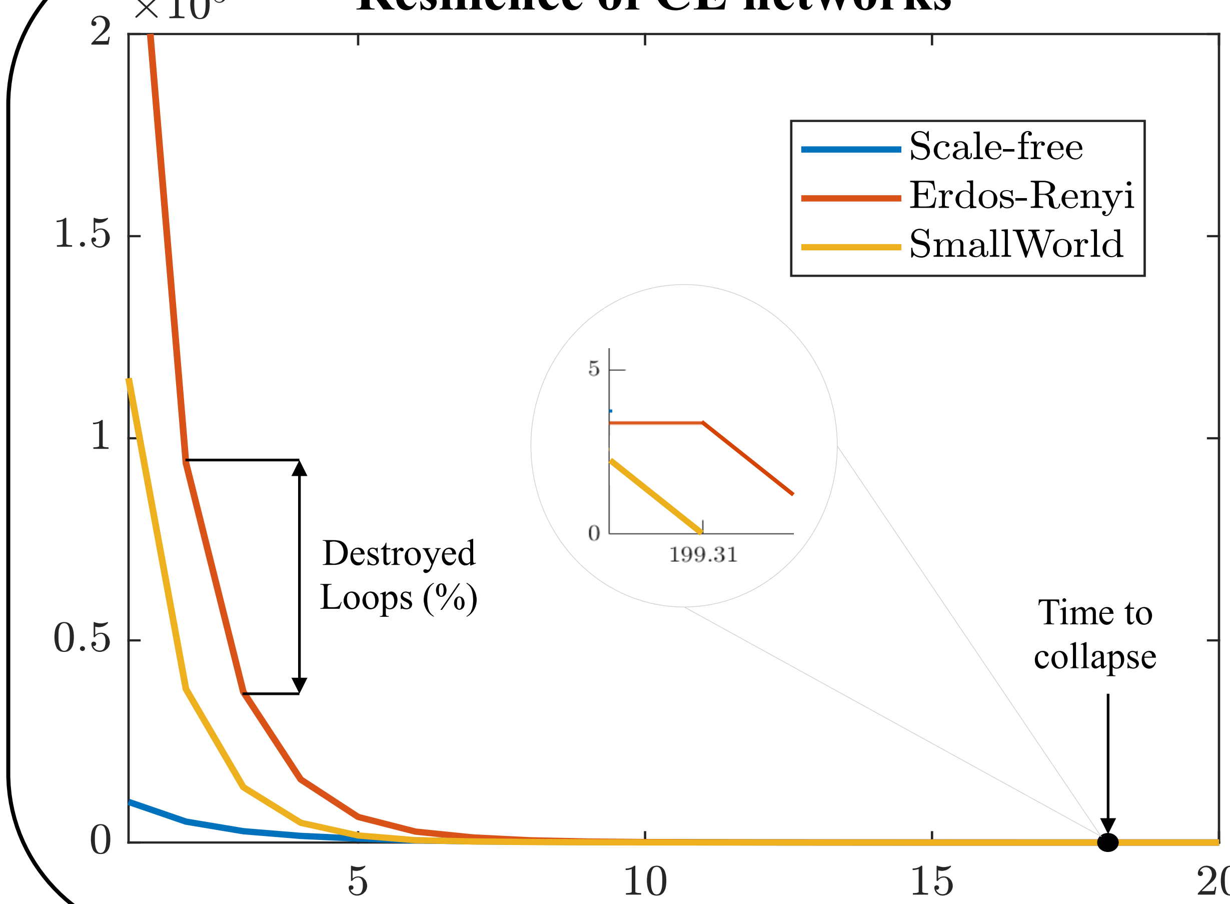


Disruptions

- Random Node/link
- Target Node/link
  - Betweenness Centrality
  - Out-/In- Degree Centrality



Resilience of CE networks



The importance of the structural pattern for the resilience of circular economy networks: A network-based approach

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Abstract

This paper investigates the resilience of circular economy (CE) networks. By adopting a graph theory approach, a novel simulation model is developed to simulate the resilience performance under the effect of multiple types of disruptions. Simulation analyses are carried out to analyse the effect of the structural pattern of the CE network on resilience by comparing the performance across scale-free, small-world, and Erdos-Renyii -like patterns. The results confirm that the structural pattern affects resilience. In particular, they show that CE networks characterized by a scale-free pattern absorb random-placed disruptions better than the others, while CE networks characterized by a small-world pattern are more resilient to target-placed disruptions.

Keywords: *Circular Economy network, resource loop, resilience, network pattern*

1. Introduction

Circular Economy (CE) represents a new economy model fostering the sustainable development of current and future society (Awan and Sroufe, 2022; Corona et al. 2019). It prescribes all the stakeholders involved in production and consumption activities to replace the *take-make-dispose* paradigm with a novel one, combining "*restorative and regenerative*" processes (EMF, 2013). These are designed to maintain technical materials in the system at their highest utility and value for as long as feasible (restorative) and to return biological materials to nature (regenerative), directly and safely (Morseletto, 2020).

The collaborative adoption of CE principles by companies leads to the emergence of CE networks. Examples of CE networks include industrial symbiosis networks (Fraccascia et al. 2017; Van Beers 2008; Van Beers et al. 2009), eco-industrial parks (Alonso-Munoz et al. 2021), circular networks for recycling (Berlin et al. 2022; Braz and de Mello et al. 2021; Schwarz and Steininger, 1997), circular networks for remanufacturing (Guidat et al. 2015), circular networks for utility reuse (Van Beers et al. 2009), and circular networks for repair (Fachbach et al. 2022; Spekkink et al. 2022; Wieser and Troger, 2018). In these systems, companies from different industrial sectors exchange resources (material, energy) for a simple purpose as increasing resource efficiency by reuse, or more complex ones such as extracting new value by maintenance, repair, refurbish, remanufacture, and recycle (Montag, 2022).

In the current competitive and turbulent environment, CE networks are threatened by multiple disrupting events that undermine their ability to create and deliver circular value. In addition to the common disruptions threatening the stability of industrial firms, such as natural events or industrial accidents, CE networks are also vulnerable to further sources of risks such as the criticality of secondary raw materials, the uncertainty of end-of-life material volume, and the reverse logistic risks. All these events can hit the operations of single firms belonging to the CE network and the links connecting partnering firms, with critical consequences for the existence of the network itself. To prevent this, CE networks have to be resilient i.e., able to "*protect and sustain*" economic, environmental, and social values, created through circular business models, from disruptive events (De Angelis, 2022).

Despite the vast literature on supply network resilience (Ivanov, 2017; Datta, 2017; Azadegan and Dooley, 2021; Wiedmer et al. 2021; Dolgui et al., 2018; Kim et al., 2015; Giannoccaro and Ifthikar, 2022), only basic argumentations have been provided so far specifically referring to the resilience of CE networks. Recent studies limit to note that CE networks are more resilient than traditional (linear) supply networks since the implementation of remanufacturing, reuse, and recycling strategies reduce their dependency from external supply sources and hence their vulnerability to the corresponding shortages (Bag et al. 2019; Awan et al. 2020; Fisher et al. 2020; Baars et al. 2021). On the contrary, studying the determinants of CE network resilience is still at an infant stage. They remain being investigated mainly in the context of industrial symbiosis networks (Chopra and Khanna 2014; Fraccascia et al. 2020; Zhu and Ruth 2013; Fraccascia et al. 2017). From these studies, it emerges that the structural features of CE networks i.e., network redundancy (Chopra and Khanna 2014; Fraccascia et al. 2020), network size, density of resource exchange (Zhu and Ruth 2013), and structural- and symbiosis- level diversity (Fraccascia et al. 2017), strongly affect its resilience.

A further important structural feature of a network is the pattern, which describes which firm interacts with whom. It has not been investigated as determinant of CE network resilience so far, although previous studies have shown it affects the resilience of traditional supply networks (Mari et al. 2015; Arora and Ventresca 2018; Ivanov, 2017; Dolgui et al., 2018; Tan et al. 2020). However, understanding how this influences the resilience of CE networks is important since empirical evidence confirms that CE networks can exhibit different structural patterns, such as the scale-free -like pattern observed in the Kalundborg symbiosis network and the Guangxi Guigang Eco-Industrial Park (Wang et al. 2018), the small-world pattern shown by water recycling systems (Xu et al. 2019), and random pattern such as for the Styria' Eco-industrial network (Ashton, 2017).

In this study, we intend to address this research gap and investigate how the structural pattern influences the resilience of CE networks. We conceptualize CE network structures by focusing on the resource loops i.e., the circular resource flows resulting from the implementation of CE strategies. In literature, previous scholars have commonly distinguished between closed loops i.e., through which post-consumption products circulate back in the same industrial sector (Kara et al. 2022; Braz and de Mello, 2022; Farooque et al. 2019), and open loops i.e., through which different waste and by-product streams circulate into industrial sectors originally separated (Ghisellini and Ulgiati, 2020; Albino et al. 2016). Less investigated is the distinction between short and long resource loops (EMF, 2013; Wieser and Troger, 2018). *Short* loops are characterized by a limited number of actors and can be usually associated with the inner cycles resulting from reuse, repair, remanufacture, and/or recondition strategies. *Long* loops, also identified as outer circles, involve a higher number of actors usually implementing recycling strategies (Montag 2022; Ang et al. 2021; Santa-Maria et al. 2021). This distinction is important since, as noted by The Ellen MacArthur Foundation, the "*power*" of short loops is much larger than that of long loops (or *outer* circles), due to a higher cost saving in terms of material, labour, energy, and capital needed to carry out the circular activities (EMF, 2015; Wieser and Troger, 2018).

All the resource loops are fundamental to provide resource circularity and preserve the functions of CE strategies. When the CE network is threatened by disruptive events, resource loops can be destroyed, which in turn reduce the ability of CE network to provide the circular value.

Since any structural pattern of the CE network contains resource loops, even though differently distributed, we investigate how this influences the network's ability to preserve the number of resource loops after the occurrence of disturbances i.e., its resilience.

To accomplish this aim, a novel agent-based model for CE networks is developed to computed resilience performance. By drawing on previous network approaches, the CE system is described using graph theory as a set of firms (nodes) and inter-firm business relationships (links). The resource loop is defined as circular path starting from a node and returning to the same node. The number of resource loops characterizing the CE structure is computed for a given structural pattern. When disruptions occur, a number of resource loops are destroyed. Resilience is computed in percentage of the number of resource loops preserved and by the time required to all resource loops to be destroyed (i.e., CE collapse). Numerical simulations are carried out to compare the resilience of three structural patterns i.e., characterized by scale-free, Erdos-Renyii, and small-world -like properties, against different types of disruptions occurring on random and target nodes and links of the CE networks. The results confirm that the network pattern influences the resilience of CE networks. In particular, CE networks characterized by a scale-free resource pattern better absorb random-placed disruptions, as proven by the lower percentage of loops destroyed than those occurring in other CE network patterns. Instead, under target-placed disruptions, CE networks characterized by a small-world resource pattern are the most resilient. For each type of resource pattern, the most severe disruptions are also identified.

This study provides multiple contributions. First, it advances the conceptualization of CE networks by focusing on short and long resource loops resulting from the implementation of CE strategies. Second, this study contributes to the still infant literature on CE network resilience by relating this to the network's ability to preserve internal resource loop structures from disrupting events and investigating the antecedent role of the structural pattern. Third, the obtained results are, to the best of our knowledge, the first ones showing how resilience varies across different CE network structures i.e., those characterized by *scale-free*, Erdos-Renyii, and *small-world* -like properties. These permit us to draw practical implications for the design and management of CE networks that are resilient to random- and target- placed disruptions.

The rest of the paper is organized as follows. Section 2 provides the literature background on CE networks (2.1.), the resilience of CE networks (2.2.), and the structure of CE networks (2.3.). In section 3, we present the research methodology by describing how we model a CE network (3.1.), the disruptions (3.2.), and the resilience performance (3.3.). Section 4 is devoted to simulation analysis (4.1.) and model validation (4.2.). Section 5 presents the results, while in Section 6 result discussion and concluding remarks are finally given.

2. Literature background

2.1. Circular Economy networks

Circular Economy (CE) is a new production and consumption paradigm replacing the unsustainable *take-make-use-dispose* economy model. CE proposes a value-oriented transformation approach to maintain resources at the "*highest utility and value*" for as long as feasible and minimise leakage out of the systems. In a CE, production and consumption systems operate in a "*restorative and regenerative*" way through dual-loop structures combining closed- and open- loop resource flows to restore technical materials into the same or different industry by repairing, reusing, remanufacturing, refurbishing, and recycling (EMF, 2015) and reintegrate biological nutrients into nature directly and safely (De Angelis et al., 2018). The implementation of CE occurs in networks where multiple stakeholders operating in different sectors, through collaborative relationships, can exchange resources and design self-regenerative processes. In CE networks there are both primary resources moving along the linear supply chain as well as the end-of-life products, wastes, and by-products, which circulate back to companies, to pursue CE principles (De Angelis et al., 2018). Consistently, Vlajic et al. (2018) defined a CE network as a set of "*connected organizations involved in the design and management of value adding processes and value recovery of a product, component, or material*".

In literature, the most investigated examples of CE networks are the Industrial Symbiosis Networks (ISNs) and Eco-Industrial Parks (EIPs) (Alonso-Munoz et al. 2021). These have similar purposes i.e., closing the loops of manufacturing processes by transforming by-products and waste into secondary feedstocks primarily by recycling and reusing. In practice, synergistic interactions are established between two collaborative parties, playing in the same or different industry sectors, to physically exchange resources e.g., materials, energy, services and facilities (Lombardi et al., 2012; Baldassarre et al., 2019). End-of-life resources are thus kept in loops for as long as feasible and, at the same time, the need for primary raw materials, the waste disposal rate, and the production of emissions can be reduced. Recently, other forms of networks pursuing CE principles are discussed by scholars. CE supply networks (CESNs) provide focal companies with an increased access to secondary raw materials (Braz and de Mello 2021). CESNs emerge from the integration and coordination of all the stakeholders from different supply chains and can be classified based on the purpose they are designed for. In recycling networks, waste picker cooperatives, reverse logistics providers, scrap dealers, and waste recycling companies collectively operate to collect waste streams from multiple industry sectors, and transform these into new resources, with equivalent, higher- (upcycling), and/or lower-level properties (downcycling), to be used again for the same and different purpose (Bocken et al. 2016). Recently cited examples include the Swedish network for steel recycling (Berlin et al. 2022), or the Brazilian network for biogas/fertilizer production from sugarcane by-products (Braz and de Mello et al. 2021), or even the African network for recovering precious metals from jewellery recycling (Braz and de Mello et al. 2021). Remanufacturing networks aim at restoring a "non-functional, discarded, or traded-in" product to a "like-new" status (Guidat et al. 2015; Chen et al. 2019) characterized by original performance specification. These processes require the collaboration of diverse stakeholders including supplier firms, to carry out disassembly operations on used products and provide raw materials when needed, independent remanufacturers and original equipment manufacturers, carrying out specific activities as part cleaning, inspection, re-fabrication, and testing, retailers and end users, responsible for collecting used products, and logistic operators, responsible for their transportation activities (Guidat et al. 2015). In repair networks, multiple repair enterprises e.g., independent repair shops (Lechner and Reimann, 2015), repair service providers, providers of information on or spare parts/tools for repairing cooperate with final customers and retailers to extend the life cycle of broken products and spare parts, and to ensure their successful reuse (Fachbach et al. 2022; Lechner et al., 2021; Wieser and Troger, 2018).

Given that companies increasingly operate in dynamic and turbulent business environments, the effectiveness of CE strategy implementation in CE networks can be threatened by disrupting events. For this reason, investigating the resilience of CE networks is becoming an urgent need.

2.2. Resilience of CE networks

Resilience is a complex property of a variety of organizational systems, such as operational teams (Giannoccaro et al. 2018; Hartwig et al. 2020; Massari et al. 2021), single firms (Iftikhar et al. 2021), and supply chains/networks (Albeetar et al. 2022; Pettit et al. 2010; Tukamuhabwa et al. 2015; Ivanov and Dolgui, 2020; Massari and Giannoccaro, 2021; Giannoccaro and Iftikhar, 2022). Since the first study by Holling (1973), its multidimensional nature has been recognized, leading to the development of two main schools of thoughts. The first supports a *static* conceptualization defining resilient that system able to absorb disturbance and bounce back to the original equilibrium state, maintaining its core functions when shocked (Bhamra et al., 2011). The higher the magnitude of disturbance that a system can absorb before a structure redesign is needed, the higher the system's resilience (Holling, 1973). The second school adopts a *dynamic* conceptualization and focuses on the system's ability to evolve over time, moving towards the original, but even new, more favourable equilibrium states (Carvalho et al., 2012). Over the course of years, the different facets of resilience have emerged. In supply chain management literature, earlier studies defined it as the system's ability to react to unexpected events, to restore normal operating conditions (Sheffi et al., 2003), to return to its original state or move to a new, more desirable one after being disturbed (Christopher and Peck 2004). The dynamic nature has emerged in later studies through e.g., the adaptive capability to prepare for unexpected events, react to disruptions, and recover from them by maintaining continuity of operations and control over structure and function (Ponomarov and Holcomb 2009); or the dynamic ability to survive, adapt, and grow in the face of turbulent change (Pettit et al., 2010). According to the theory of complex adaptive systems, recent studies have conceptualized supply chain resilience as a system-level property emerging from the adaptive and self-organized behaviours of the individual firms while facing with disruptions (Giannoccaro and Ifthikar, 2020; Massari et al. 2021). Ivanov (2020) studied resilience through the construct of supply chain *viability* that is the ability to adapt and react to changes for long-term survival based on sustainable development. These concepts recur also in the definition of ecological resilience manifested by industrial symbiosis networks (Chopra and Khanna, 2014; Allenby and Fink, 2005; Fiksel, 2003, 2006; Korhonen and Seager, 2008; Zhu and Ruth, 2013; Fath et al., 2019). In fact, it is defined as the ability to "maintain eco-efficient material and energy flows under disruptions" (Zhu and Ruth, 2013), or to "absorb disruptions, while maintain its structure and function" (Chopra and Khanna, 2014), or even to "maintain the functioning of network elements after disruptions" (Zeng et al. 2013; Li et al. 2015).

Less investigated is the resilience of CE networks. Awan et al. (2020) observed that none of the existing definitions of CE include the concept of resilience. They argue that circular business models, by promoting the use of restorative and regenerative resources, enhance firm's resilience against resource scarcity related risks. A more rigorous definition is recently provided by De Angelis (2022) who conceptualized the firm's resilience as the ability to "protect and sustain" social economic and environmental values created through circular business models, threatened by disruptive events.

Few studies have investigated the antecedents of the resilience of CE networks. On firm- and industry- level, Bag et al. (2019) argue that dynamic remanufacturing capabilities i.e., '*the ability to produce remanufactured parts as per market demand using existing resources and current capacity of the plant*', can enhance resilience by reducing the dependence on raw material thanks to increased adaptability and flexibility. Baars et al. (2021) examine the effectiveness of supply diversity on the manufacturing process of electric vehicle batteries. Through reuse and recycling, firms can reduce the high dependence on sourcing cobalt (a by-product of mining nickel and copper). Fisher et al. (2020, p. 97) argue that '*recovering, reusing, recycling and valorising waste resources … will further increase the resilience of manufacturing systems from disruptions in the supply chain'*.

Studies on resilience of industrial symbiosis networks have highlighted the antecedent role of the network features. High level of network redundancy i.e., having multiple links providing similar resources, are found to positively influence network resilience by favouring flexibility and adaptive capability to disrupting events (Chopra and Khanna 2013; Fraccascia et al. 2020). As studied by Zhu and Ruth (2013), increasing the number of firms and the density of links for resource exchange increases network's resistance to random disturbances. Fraccascia et al. (2017) analysed the effect on ISN resilience of the industrial symbiosis diversity (the number of by-products exchanged in the network), the firm diversity (the number and quantity of waste exchanged by that firm) and the waste ubiquity (the number of firms producing and using a certain waste). They proposed a novel index showing that ISN resilience increases at high levels of waste ubiquity (at equal firm diversity), firm's diversity (at equal waste ubiquity), and network diversity.

In line with these studies, we are interested to examine how CE network pattern influences its resilience.

2.3. The structure of CE networks

2.3.1. The CE resource loops

CE networks extend linear supply chains by integrating resource loops involving actors enabling the circularity functions (see Figure 1). A common classification of the CE networks distinguishes among closed-loop, open-loop, and hybrid-loop networks.

Closed-loop CE networks consist of post-consumption products and by-products cycles, circulating back in the same network with the direct involvement of the focal companies (Kara et al. 2022; Braz and de Mello, 2022; Farooque et al. 2019). For example, Kodak single-use cameras are collected by film developers and returned to the focal company to be reused for the original purpose (Berlin et al. 2022; Guide and Van Wassenhove, 2009; Akçali and Çetinkaya, 2011). Construction machineries circulate back, through closed loops, to the original equipment manufacturer to undergo the entire remanufacturing process including cleaning, dismantling, sorting, recovery and reassembling (Yi et al. 2016). Examples are spread across different sectors (MahmoumGonbadi et al. 2021).

Open-loop CE networks are characterized by resource flows of recovered products and by-products, circulating between networks originally separated, such as in the case of industrial symbiosis connecting companies in different supply chains. An example regards the UK Humber Industrial Symbiosis Program where multiple firms from different sectors e.g., automotive, agricultural, aviation etc., purchased glycerol as new input material of their internal production processes. Other examples come from the industrial symbiosis experienced by Italian companies able to e.g., produce pavements by recycling end-of-life tyres of commercial cars, or to use food by-products to produce luxury goods or textiles (Ghisellini and Ulgiati, 2020). Albino et al. (2016) provide a comprehensive description of resource exchange in most-important industrial symbiosis networks.

Hybrid-loop networks show both types of loops i.e., the closed cycles of recovered products circulating back to the actors in the same networks and the open cycles involving other companies in different supply chains (Braz and de Mello, 2021). These have been observed in distinct CE supply networks e.g., those for recycling batteries, precious metals, and cardboard box materials (Braz and de Mello, 2021).

From a structural point of view, it is relevant to characterize the resource loops also in terms of the number of actors involved. Two classes can be categorized i.e., short and long loops (Montag 2022; Ang et al. 2021; Santa-Maria et al. 2021). Short loops involve a limited number of firms. A short loop is made up of at least two firms e.g., in industrial symbiosis networks (Fraccascia et al. 2020), but can involve also other few enterprises typically operating close to the consumer (original equipment manufacturer, service provider) and the consumer itself. These firms operate to increase resource efficiency directly from the product design phase i.e., by means of reduce, rethink and reuse CE strategy, and/or extend product life cycle by collecting end-of-life resources and recover them i.e., by means of repair, remanufacture, and recondition CE strategy. For example, in CE networks for remanufacturing, the key activities can be integrated in the original equipment manufacturer processes, relegated to a sub-contractor, or carried out by a competitive remanufacturer. Short loops are common in real CE networks e.g., that developed by ABB company to repair damaged robots, or that developed by Colborne Foodbotics company to remanufacture end-of-life industrial packaging machines. In both the cases, the short loops involve the focal company, who purchases end-of-life products from global consumers, and the service provider, who carries out the specific activities for resource recovery. Other short loops are observed in the CE network developed by UK company Reconome for reconditioning electronic products involving the direct consumer and the company.

Instead, long loops involve a higher number of firms e.g., waste collectors, waste treatment companies, part/raw material suppliers, etc. All these firms operate to extract new value from waste e.g., transforming them into secondary raw materials, by means of recycling CE strategy. An example of long loop is observed in the CE network for battery recycling (Braz and de Mello, 2021). It usually involves manufacturers (of cells, batteries and electric cars), maintainers, dismantlers, remanufacturers, recyclers, and users. The following activities are carried out by companies: storage and securing of disused accumulators from their respective sectors of origin, also providing for the recovery of the residual energy contained; disassembly and related pre-treatment through innovative technologies that, taking advantage of robotic automation, promote the efficiency of processes and the performance of activities in compliance with the highest safety standards; health check of individual cells and/or modules, through innovative methods of residual life estimation, to identify components that are still usable; re-assembly of reusable cells and/or modules and the production of new energy storage packs, for stationary applications. A further example is observed in the CE network for plastic recycling. Here, a long loop involves multiple actors: the waste picker (for collection and recovery activities), the scrap shop and franchise (material separation/sorting), the granule producer (waste-to-material conversion into plastic granules), the manufacturer (granule-to-packaging conversion), and the brand that obtains the packaging and places it in the market for consumers. The CE network by Tetra Pak is also composed of open and long cycles (Batista et al., 2018). Eight recycling companies receive packaging disposed of from Tetra Pak and food processing companies. In addition, small collection centres play the important role of hub channels by concentrating flows of used beverage cartons from a large number of retailers, end consumers, and individual waste collectors. Recyclers are able to turn used beverage cartons into secondary raw materials that are fed back into a secondary market.

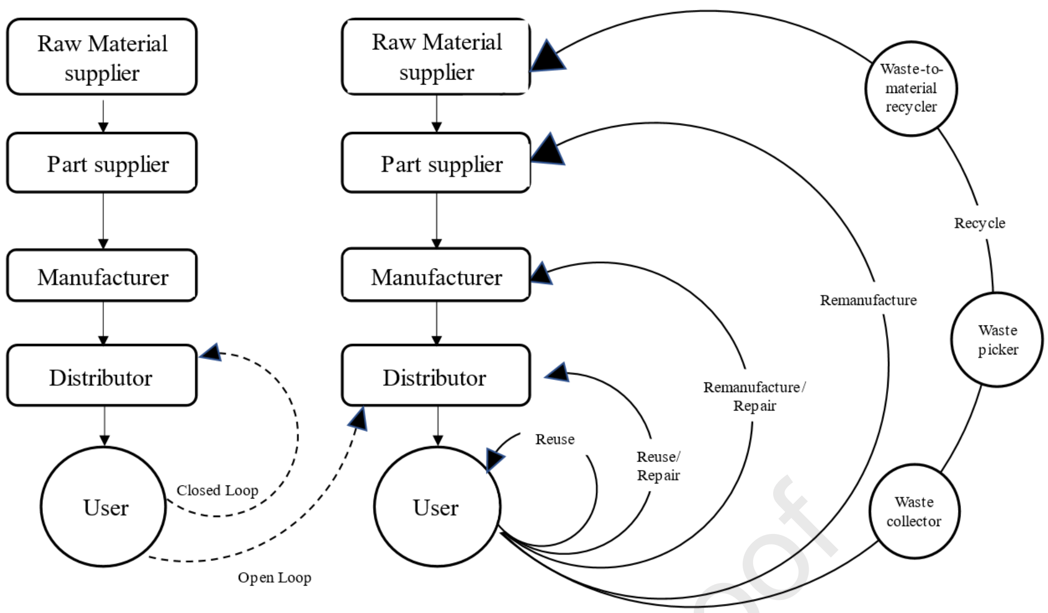

Figure 1: *The resource loops in CE.*

2.3.2. The structural patterns of the circular economy networks

In literature, studies have employed network metrices to examine the archetypes of CE networks. The most discussed patterns are three: the *scale-free*, *random*, and *small-world* (Basole & Bellamy, 2014; Kim et al., 2015; Nair & Vidal 2011; Zhao et al. 2011).

Scale-free patterns display a power-law -like node degree distribution (Barabási and Albert, 1999). This implies few nodes having many connections, while most of the other nodes having only few connections. This property is observed in self-organized ISNs where source (end) enterprises are characterized by high value of outdegree (indegree) connectivity. As an example, in Kalundborg symbiosis network six large companies ("*anchors*") have established a high number of long-term symbiotic relationships given the abundant resources possessed, which can be used as secondary raw materials by many partnering firms. The resulting network is characterized by a dense core structure, given the high centralization of enterprise firms, and less dense peripherical structure, given the low number of relationships established by the rest of the companies. A similar structure is observed in Guangxi Guigang (Wang et al. 2018). Heterogeneous node degree distributions characterize other industrial symbiosis eco-networks e.g., the Yixing Economic and Technological Development Zone, where few hub firms, referring to the photovoltaic production companies, chemical plants, and textile companies, manage the key resource flows (acetic acid, liquid caustic soda, and coal) through a high number of symbiotic relationships.

Random patterns are characterized by homogeneous node degree distribution i.e., where the majority of nodes have the same number of relationships (Erdős and Rényi, 1960). An example is provided by the Styria' Eco-industrial network where small and specialized firms ("*scavengers*") are all involved in recovery activities on multiple waste streams (Ashton et al. 2017).

Small-world patterns exhibit a high clustering coefficient and a small average shortest path length (Watts and Strogatz, 1998). The structure of small-world networks is commonly organized into small clusters and few links shortening the distance between any two companies in each cluster. This structure may be crucial for resource exchange as observed in Daqing Eco Industrial Park (Wang et al. 2021), the network for water recycling in EIPs (Xu et al. 2019).

To the best of our knowledge, no other studies have investigated how the structural pattern of the CE network, by affecting the resource loop structure, influences the resilience to external shocks. The conceptual model we intend to investigate is reported in Figure 2.

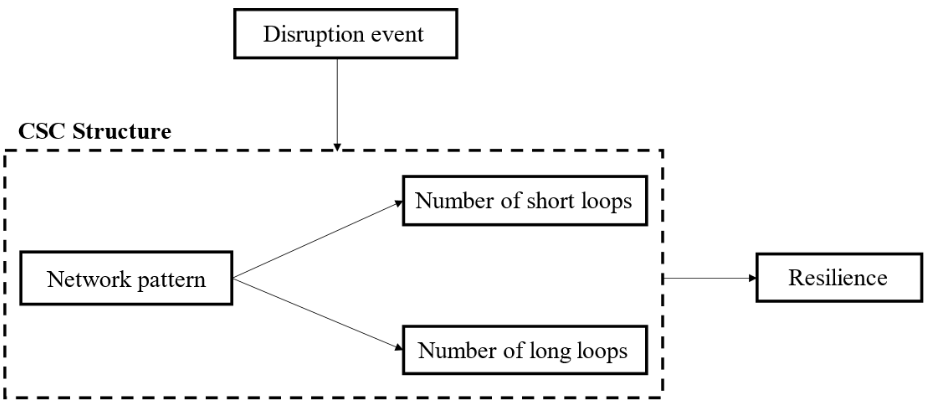

Figure 2: *Conceptual model under investigation.*

3. The CE network simulation model

We adopted the agent-based numerical simulation as research methodology. This choice is supported by three reasons. First, whereas analytical models may not be capable of handling complex problem settings (Dolgui, et al., 2018), simulation is an effective tool to easily describe complex systems i.e., by means of the agents and their interaction patterns, and examine the dynamic behaviours. Second, simulation permits us to investigate non-linear phenomena occurring on complex network structures which may be intractable by equation-based models. Third, simulation is proven suitable in investigating the resilient property of complex systems including supply chains (Massari and Giannoccaro, 2021), supply networks (Nair and Vidal, 2011; Giannoccaro and Ifthikar, 2020; Kim et al., 2015), and industrial symbiosis networks (Yazan and Fraccascia, 2020). In the following sections, a detailed description of the developed agent-based model is given.

3.1. The model of the CE network

We model a CE network as a directed unweighted graph *G (N, l)* where N refers to the number of nodes (firms in the network) and *l* to the number of edges (resource flows between firms). Edges are directed, meaning that resources flow from the *i-th* firm (seller) to the *j-th* firm (receiver). This graph-based approach is consistent with previous studies investigating the resilience of ISNs and supply networks (Wang et al. 2017; Wang et al. 2018; Zeng et al. 2013; Kim et 2015; Choudhary et al. 2021; Pagano et al. 2019; Zhao et al. 2019).

An adjacency matrix A defines which firm sends resources to whom. This matrix corresponds to the structural pattern of the CE network, since it takes into account the specific distribution of links among the companies. An exemplar of directed unweighted random graph and its adjacency matrix is given in Figure 3.

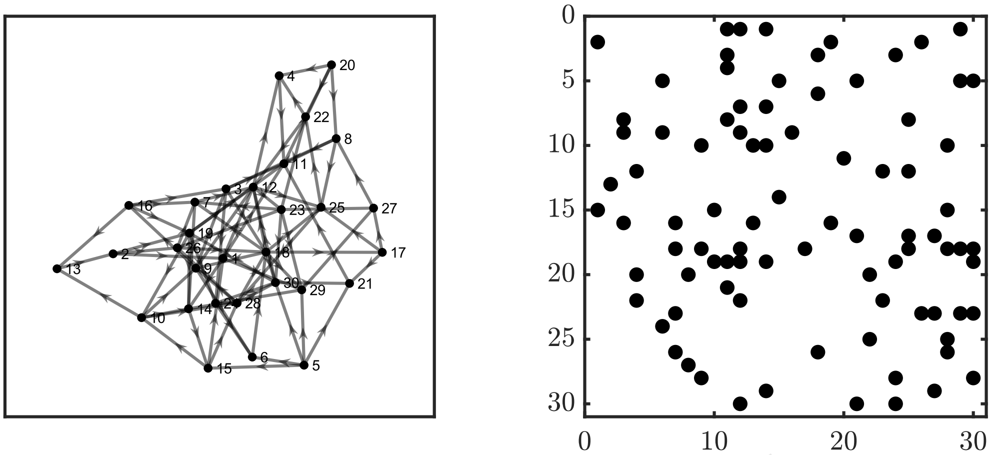

Figure 3: *Exemplar of a directed unweighted random graph (on the left) with M=30 nodes, a uniform node degree distribution, and density* $\sigma = 0.2$*; and its adjacency matrix (on the right).*

Any structural pattern includes a resource loop structure. A resource loop structure is made up of a number of short and long loops (see Figure 4). A loop is a directed walk $W(N_o, N_e)$ starting from node N_o (origin node) and ending at N_e (end node), where the origin node coincides with the end node. Thus, once specified the pattern of a CE network, a set of closed paths can be computed. Consistently with the real-world CE networks described in Section 2.3.1., we distinguished between two types of loop structures: short loops involving $2 \leq N \leq 3$ firms and long loops involving $N > 3$ firms.

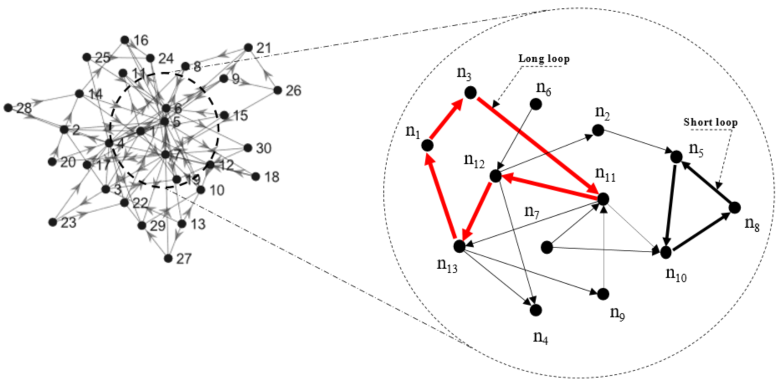

Figure 4: *Examples of short and long loops in a given CE network structural pattern.*

3.2. The model of disruptions

We consider that CE networks operate in turbulent environments characterized by frequent and unpredictable disruptions. Disruptions can occur at the level of firm (node) and/or at the level of resource flow (link). They can be categorized as random i.e., when regarding a random node or link in the network, and targeted i.e., when occurring on a specific node or link in the network. By mapping CE systems into networks, these disruptions can be modelled by removing random or target nodes and links (see Figure 5).

To define target nodes/edges, we compute three network metrics: node betweenness centrality, in-degree, and out-degree. Betweenness centrality is the number of shortest paths, between every node pair, that pass through the node of interest (Carrington and Scott, 2011). Thus, the higher the betweenness centrality, the higher the extent to which that node lies on shortest paths between other nodes. In CE networks, this metrics identifies the nodes expected to receive/send resources more efficiently. The node in-degree (out-degree) is the number of incoming (outcoming) links associated with a specific node (Kim et al. 2015). In CE networks, this metrics identifies the nodes expected to receive/send a high number of resource streams. A target node is that characterized by the highest metric value. A target edge is that connecting two target nodes. These network metrics permit us defining different types of a CE disruption and modelling them correspondingly. Finally, the number of removed node (or link) permits us modelling the impact of a disruption.

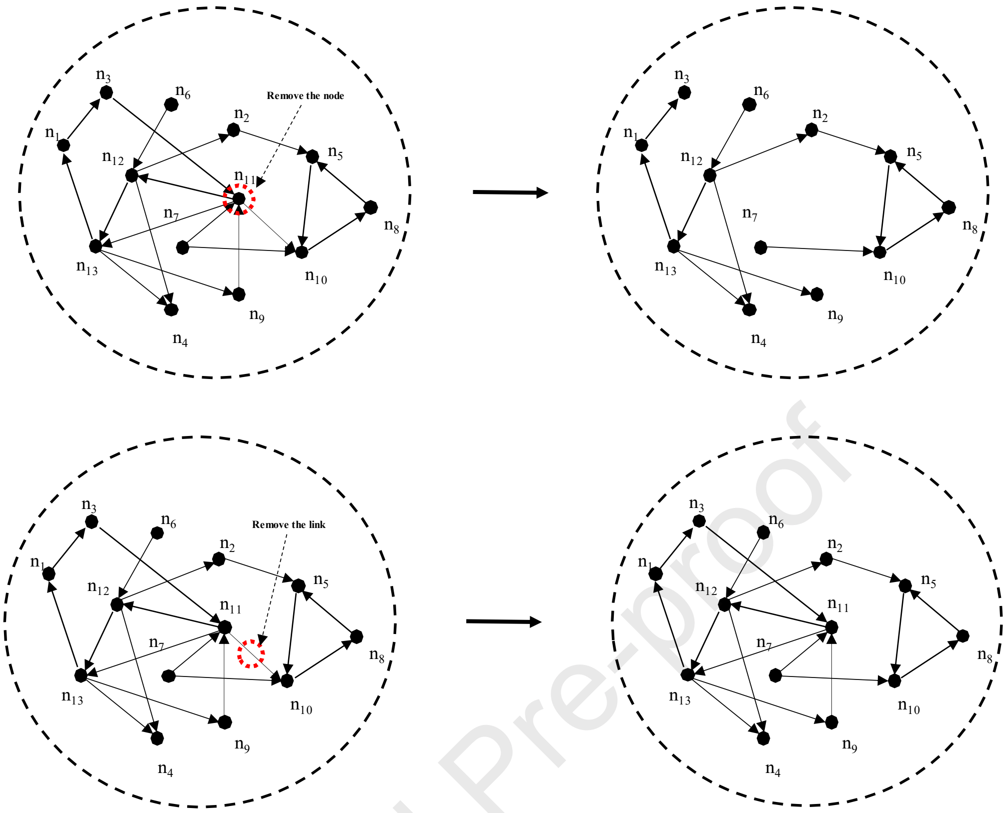

Figure 5: *A graphical illustration of a single node disruption (top), and single link disruption (bottom).*

3.3 The model of resilience performance

We conceptualize resilience of a CE network as the ability of the system to maintain circularity functions once disrupted, by preserving the resource loop structures from collapse. Coherently, we adopted two distinct measures.

The first refers to the number of resource loops destroyed after the occurrence of a disruption in percentage to the total number of loops originally characterizing the CE network. The higher the percentage of loops destroyed, the lower the resilience of the CE network. Since all nodes and edges included in a loop are fundamental for its functioning, we considered that a loop is destroyed, and hence collapses, when it lost a node or an edge.

The second measurement is computed by simulating that the CE network is exposed to disruptions occurring consecutively over time i.e., one at each simulation step. It refers to the time to collapse i.e., how long a CE network resists to sequential disruptions before all the resource loops collapse. The higher the time to collapse, the higher the resilience of the network.

The percentage of loops destroyed and the time to collapse are computed by executing the simulation steps illustrated in Figure 6.

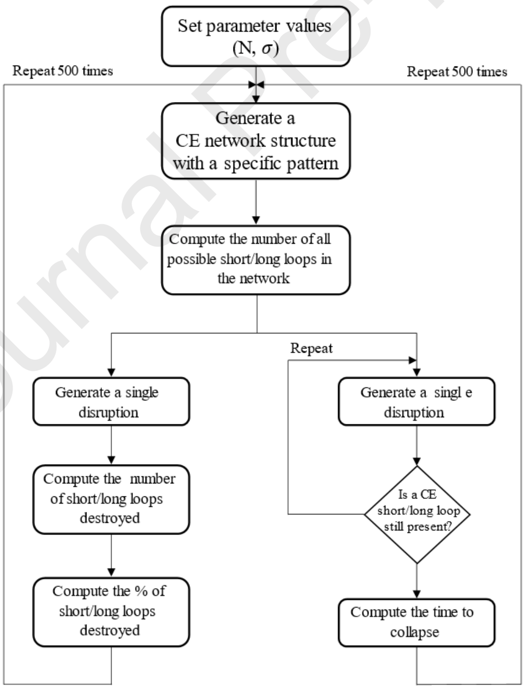

Figure 6: *The steps of the simulation model.*

4. Simulation Analysis

We consider a network made up of $N = 30$ firms. To analyse the effect of network pattern, we run the model on three networks characterized by a scale-free, small-world, and Erdos-Renyii pattern (see Figure 7). The density is fixed and equal to $\sigma = 0.1$. The choice on the number of firms is supported by empirical data concerning repair networks (Spekkink et al. 2022), recycling networks (Schwarz and Steininger, 1997), networks for by-products/utility reuse (Van Beers et al. 2009), ISNs and ecosystems (Albino et al. 2016; Zhu and Ruth, 2013). To set the density we referred to the studies reporting the number of circular relationships occurring within real CE networks (Van Beers 2008; Schwarz and Steininger, 1997; Zhu and Ruth 2013). We simulated the performance of the CE network structures in 36 different environments, resulting from the combination of 12 types of disruptions and 3 values of disruption's impact. To ensure statistically significance, each scenario is replicated 500 times, starting from a different graph with the same structural property (size, and density). Table 1 summarizes the model parameters, the operationalizations, and values used for simulation.

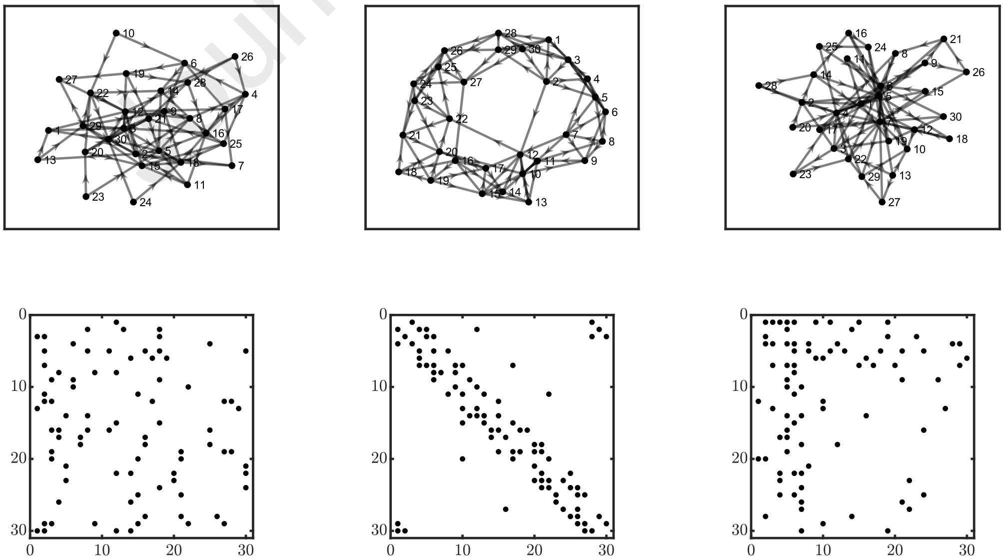

Figure 7: *Exemplar of three network structures ($N = 30, \sigma = 0.1$) characterized by a scale-free (a), small-world (b), and Erdos-Renyii (c) node degree distribution, and the corresponding adjacency matrices.*

Table 1: *The model parameters, their operationalization, and the values used for numerical simulations*

Model Parameter	Operationalization	Parameter Value
Network pattern	Node degree probability distribution	Scale-free
		Erdos-Renyii
		Small-world
Disruption type	Type of selection	Random
		Targeted (Betweenness Centrality)
		Targeted (Indegree Centrality)
		Targeted (Outdegree Centrality)
	Disrupted element	Node; Link
Disruption impact	Num. of disrupted element	1, 2, 4
Cycle type	Num. of firms involved in the circular flow	Short ($2 \leq N \leq 3$)
		Long ($N > 3$ firms)

5. Results

5.1. The percentage of resource loops destroyed in CE networks

Table 2 reports the results of simulation. We now analyse the effect of network pattern on the resilience of CE networks, by comparing the percentage of loops destroyed across the network patterns. Results show that scale-free patterns are more robust than small-world and Erdos-Renyii ones to both removal of nodes and links. In almost all the simulated cases, the percentage of loops destroyed in scale-free patterns is lower than that in small-world and Erdos-Renyii ones. For example, when two random nodes in scale-free networks are removed, the percentage of long (short) loops destroyed is 64.5% (18.4%), compared to Erdos-Renyii networks, where the percentage increases to 77.5% (19.9%); and small-world networks, where the percentage increases to 84% (19%). On average, when random nodes are removed, the percentage of disrupted long (short) cycles internal to scale-free networks is 64.4% (21.8%), while those internal to small-world and Erdos-Renyii networks is respectively 81% (21.6%), and 74.3% (22.3%).

Similarly, when random links are removed, the percentage of long (short) loops destroyed internal to scale-free networks is 29.5% (7.7%), while those internal to small-world and Erdos-Renyii networks is 38.4% (7.5%), and 34.5% (7.8%), respectively. For example, when two random links in scale-free networks are removed, the percentage of long (short) loops destroyed is 26.6% (6.2%). When the same disruption occurs on Erdos-Renyii networks, the percentage increases to 31.6% (6.9%); whilst when the disruption occurs on small-world networks, the percentage increases to 36.8% (6.6%). Given the heterogenous distribution of resource links in scale-free patterns (see section 2.3.2.), a random-placed disruption affects, with a high (low) probability, the high (low) number of peripheral (anchor) firms, thus leading to the collapse of a low (high) number of loops. Across all the simulated cases, the most severe disruption is that occurring on small-world -like networks, leading to the collapse of long loop structures by the removal of four random nodes, as proven by the percentage of destroyed loops equal to 96.2%.

However, when the disruptions occur on targeted nodes, small-world patterns are more robust than scale-free and Erdos-Renyii networks. For example, in the case two nodes with the highest betweenness centrality value are removed, the percentage of long (short) loops destroyed in small-world networks is 96.9% (26.4%). When the same disruption occurs on scale-free networks, the percentage of long (short) loops destroyed increases to 99.1% (73.9%) as well as, when the disruption occurs on Erdos-Renyii networks, the percentage increases to 98.2% (47.9%) instances. On average, when the nodes with the highest betweenness centrality are removed, the percentage of long (short) loops destroyed in small-world networks is 95.4% (28.8%), whilst in scale-free and Erdos-Renyii networks it increases to 97.3% (71.9%) and 96.1% (50%), respectively. Similarly, when the nodes with the highest outdegree connectivity value are removed, the percentage of long (short) loops destroyed in small-world networks is 70.3% (16.2%), while in scale-free and Erdos-Renyii networks it increases to 85.2% (36.5%) and 94.9% (64.7%), respectively. When the disruptions regard targeted links, small-world networks are still more robust than the other network structures. On average, when the links between two nodes with the highest outdegree connectivity are removed, the percentage of long (short) loops destroyed in small-world networks is 20% (2.7%), whilst in scale-free and Erdos-Renyii networks it increases to 24.2% (11.2%) and 25.1% (6.8%), respectively. This trend is confirmed except in one case. In fact, when disruptions occur on the links between the nodes with the highest betweenness centrality value, the percentage of long loops destroyed in scale-free networks is lower than that in other structures. Overall, a small-world -like pattern is beneficial for resilience, since the negative effects of a disruption remain localized into small clusters (unless the case all firms are disrupted). This leads to the collapse of only few loops, which in turn results in higher network resilience. Note that we also simulated the CE resilient performance to targeted disruptions by using in and out eigenvector-based centrality measures. Results reported in Supplementary File confirm the trends above.

We also noted that in the case of random (node and link) disruptions, the positive influence that scale-free network patterns have on the CE network resilience is more (less) pronounced on long (short) loops (see the % diff. in Table 2). Instead, in the case of targeted disruptions, the positive influence that small-world network patterns have on the CE network resilience is more (less) pronounced on short (long) loops (see the % diff. in Table 2).

495 ***Table 2:*** *The percentage of resource loops destroyed in CE networks (N=30)*

Disruption Type	Disrupted element	Disruption Impact	Cycle	Scale-Free	Erdos-Renyii	Small-world	Diff. %
RANDOM	NODE	1	LONG	42.4331	51.1429	62.8972	**32.54**
RANDOM	NODE	1	SHORT	10.6457	10.9280	9.9533	**8.92**
RANDOM	NODE	2	LONG	64.5300	77.5288	83.9568	**23.14**
RANDOM	NODE	2	SHORT	18.3831	19.9411	19.1020	**7.81**
RANDOM	NODE	4	LONG	86.3256	94.1994	96.2199	**10.28**
RANDOM	NODE	4	SHORT	36.2271	36.0883	35.7913	**1.20**
RANDOM	LINK	1	LONG	15.1106	18.6969	19.8207	**23.76**
RANDOM	LINK	1	SHORT	3.7759	3.4097	3.2563	**13.76**
RANDOM	LINK	2	LONG	26.6184	31.6437	36.7556	**27.58**
RANDOM	LINK	2	SHORT	6.2091	6.8708	6.6219	**9.63**
RANDOM	LINK	4	LONG	46.6327	53.1043	58.6014	**20.42**
RANDOM	LINK	4	SHORT	13.1822	13.2475	12.5975	**4.91**
TARGETED (BETW. CENT.TY)	NODE	1	LONG	92.9730	90.3963	90.1286	**3.06**
TARGETED (BETW. CENT.TY)	NODE	1	SHORT	50.8451	30.0360	15.4423	**69.63**
TARGETED (BETW. CENT.TY)	NODE	2	LONG	99.0889	98.1838	96.8918	**2.22**
TARGETED (BETW. CENT.TY)	NODE	2	SHORT	73.8637	47.8767	26.3519	**64.32**
TARGETED (BETW. CENT.TY)	NODE	4	LONG	99.9485	99.7639	99.1245	**0.82**
TARGETED (BETW. CENT.TY)	NODE	4	SHORT	90.9972	71.1138	44.4661	**51.13**
TARGETED (BETW. CENT.TY)	LINK	1	LONG	13.0901	22.0573	30.2361	**56.71**
TARGETED (BETW. CENT.TY)	LINK	1	SHORT	7.1673	7.1751	5.0323	**29.87**
TARGETED (BETW. CENT.TY)	LINK	2	LONG	27.3037	43.7078	58.5248	**53.35**
TARGETED (BETW. CENT.TY)	LINK	2	SHORT	14.4061	14.1897	9.8498	**31.63**
TARGETED (BETW. CENT.TY)	LINK	4	LONG	52.8317	77.4382	87.8813	**39.88**
TARGETED (BETW. CENT.TY)	LINK	4	SHORT	28.8081	24.9685	15.0839	**47.64**
TARGETED (OUT-DEG. CENT.TY)	NODE	1	LONG	87.0878	69.4120	45.9236	**47.27**
TARGETED (OUT-DEG. CENT.TY)	NODE	1	SHORT	41.4477	19.0292	6.3539	**84.67**
TARGETED (OUT-DEG. CENT.TY)	NODE	2	LONG	97.6453	88.4054	71.8013	**26.47**
TARGETED (OUT-DEG. CENT.TY)	NODE	2	SHORT	64.7535	33.8692	13.1872	**79.63**
TARGETED (OUT-DEG. CENT.TY)	NODE	4	LONG	99.8255	97.8765	93.1257	**6.71**
TARGETED (OUT-DEG. CENT.TY)	NODE	4	SHORT	87.8220	56.5100	28.9399	**67.05**
TARGETED (OUT-DEG. CENT.TY)	LINK	1	LONG	10.7650	10.5920	8.9599	**16.77**
TARGETED (OUT-DEG. CENT.TY)	LINK	1	SHORT	4.8453	2.7565	1.0734	**77.85**
TARGETED (OUT-DEG. CENT.TY)	LINK	2	LONG	20.7195	21.6151	16.2898	**24.64**
TARGETED (OUT-DEG. CENT.TY)	LINK	2	SHORT	9.1993	5.9174	2.3052	**74.94**
TARGETED (OUT-DEG. CENT.TY)	LINK	4	LONG	40.9641	43.1799	34.8195	**19.36**
TARGETED (OUT-DEG. CENT.TY)	LINK	4	SHORT	19.7338	11.6171	4.7081	**76.14**
TARGETED (IN-DEG. CENT.TY)	NODE	1	LONG	87.2464	69.2332	47.2502	**45.84**
TARGETED (IN -DEG. CENT.TY)	NODE	1	SHORT	41.7863	19.6357	6.9054	**83.47**
TARGETED (IN -DEG. CENT.TY)	NODE	2	LONG	97.6495	88.8608	73.8475	**24.37**
TARGETED (IN -DEG. CENT.TY)	NODE	2	SHORT	65.9390	33.1209	13.9641	**78.82**
TARGETED (IN-DEG. CENT.TY)	NODE	4	LONG	99.8244	98.2788	93.9603	**5.87**
TARGETED (IN -DEG. CENT.TY)	NODE	4	SHORT	87.6841	54.8884	29.7939	**66.02**
TARGETED (IN -DEG. CENT.TY)	LINK	1	LONG	10.6292	10.5818	8.1560	**23.27**
TARGETED (IN -DEG. CENT.TY)	LINK	1	SHORT	7.6793	7.6598	6.3183	**17.72**

TARGETED (IN-DEG. CENT.TY)	LINK	2	LONG	20.6738	21.8218	17.6603	**19.07**
TARGETED (IN -DEG. CENT.TY)	LINK	2	SHORT	15.3861	14.1380	8.3749	**45.57**
TARGETED (IN -DEG. CENT.TY)	LINK	4	LONG	40.5957	43.2086	35.4320	**18.00**
TARGETED (IN -DEG. CENT.TY)	LINK	4	SHORT	28.7919	19.4958	10.2886	**64.27**

5.2. The time to collapse of CE networks

Table 3 reports the simulation results. Results show that loop structures in small-world -like patterns resist to random disruptions longer than those in scale-free and Erdos-Renyii patterns. For example, in the case of double removal of random nodes, long (short) loops collapse after 9.5 (10.9) time instances. In the same cases, in scale-free network patterns, long (short) loops collapse after 9.2 (9.9) time instances; while in Erdos-Renyii network patterns, long (short) loops collapse after 9.1 (9.4) time instances. Or even, in the case of double removal of random links, long (short) loops collapse after 28.3 (31.4) time instances. In the same cases, in scale-free network patterns, long (short) loops collapse after 27.2 (26.6) time instances; while in Erdos-Renyii network patterns, long (short) loops collapse after 27.7 (25) time instances. On average, when random nodes are removed, long (short) loops internal to small-world network patterns collapse after 10.74 (12.54) time instances, while those internal to scale-free and Erdos-Renyii network patterns collapse respectively after 10.61 (11.08), and 10.65 (10.63) instances. On average, when random links are removed, long (short) loops internal to small-world network patterns collapse after 32.59 (36.03) time instances, while those internal to scale-free and Erdos-Renyii network patterns collapse earlier, respectively after 31.83 (30.97), and 31.89 (29.24) instances.

Across all the simulated scenarios, the most severe disruption is that occurring on CE networks with scale-free -like patterns leading to the collapse of long loops by the removal of four random nodes, as proven by the time to collapse equal to 5.38 time instances.

Results also show loop structures in small-world -like patterns resist to targeted disruptions longer than those in scale-free and Erdos-Renyii patterns. For example, in the case two nodes with the highest betweenness centrality value are removed, long (short) loops in small-world network patterns collapse after 6.1 (7.2) time instances. In the same cases, in scale-free network patterns, long (short) loops collapse after 3.8 (3.8) time instances; while in Erdos-Renyii network patterns, long (short) loops collapse after 4.6 (4.9) instances. On average, when the nodes with the highest betweenness centrality are removed, long (short) loops in small-world network patterns collapse after 6.48 (7.71) time instances, while those in scale-free and Erdos-Renyii network patterns collapse respectively after 3.99 (4.1), and 4.87 (5.23) instances. On average, when the links between two nodes with the highest betweenness centrality are removed, long (short) loops in small-world network patterns collapse after 18.28 (22.60) time instances, while those in scale-free and Erdos-Renyii network patterns collapse respectively after 16.01 (17.27), and 15.49 (16.92) instances. See Table 3 for additional results.

Across all the simulated scenarios, the most severe disruption is that occurring on CE networks with scale-free network pattern leading to the collapse of short loops by the removal of four nodes with the highest betweenness centrality, as proven by the time to collapse equal to 2.72. As noted in the previous section, the CE resilient performance to targeted disruptions, by using in and out eigenvector-based centrality measures, are reported in Supplementary File. Results confirm the trends above.

In all the simulated cases, the positive influence that small-world network patterns have on the resilience is more (less) pronounced on short (long) loops (see the % diff. in Table 3). On average, under random node disruptions, the time to collapse of short (long) loops in small-world network patterns increases of an amount of 15.3% (1.2%). Similarly, under random link disruptions, the time to collapse of short (long) loops in small-world network patterns increases of an amount of 18.86% (2.34%). This is true even in case of targeted disruptions.

Table 3: *Results of simulations i.e., the time to collapse of CE networks (N=30)*

Disruption Type	Disrupted element	Disruption Impact	Cycle	Scale-Free	Erdos-Renyii	Small-world	Diff. %
RANDOM	NODE	1	LONG	17.2900	17.3480	17.1860	**0.93**
RANDOM	NODE	1	SHORT	17.7980	17.0700	20.5020	**16.74**
RANDOM	NODE	2	LONG	9.1740	9.1260	9.5040	**3.98**
RANDOM	NODE	2	SHORT	9.8480	9.3560	10.9180	**14.31**
RANDOM	NODE	4	LONG	5.3800	5.4800	5.5280	**2.68**
RANDOM	NODE	4	SHORT	5.5960	5.4520	6.2020	**12.09**
RANDOM	LINK	1	LONG	53.3420	53.0580	54.5160	**2.67**
RANDOM	LINK	1	SHORT	51.9420	49.0240	60.2000	**18.56**
RANDOM	LINK	2	LONG	27.2380	27.7200	28.2900	**3.72**
RANDOM	LINK	2	SHORT	26.5940	24.9600	31.4340	**20.60**
RANDOM	LINK	4	LONG	14.8960	14.8920	14.9560	**0.43**
RANDOM	LINK	4	SHORT	14.3740	13.7300	16.4660	**16.62**
TARGETED (BETW. CENT.TY)	NODE	1	LONG	5.4840	6.7220	9.1100	**39.80**
TARGETED (BETW. CENT.TY)	NODE	1	SHORT	5.7620	7.3980	11.1220	**48.19**
TARGETED (BETW. CENT.TY)	NODE	2	LONG	3.7500	4.6020	6.1440	**38.96**
TARGETED (BETW. CENT.TY)	NODE	2	SHORT	3.8040	4.9100	7.2080	**47.23**
TARGETED (BETW. CENT.TY)	NODE	4	LONG	2.7280	3.2740	4.1980	**35.02**
TARGETED (BETW. CENT.TY)	NODE	4	SHORT	2.7200	3.3880	4.7960	**43.29**
TARGETED (BETW. CENT.TY)	LINK	1	LONG	26.1920	25.4700	29.8720	**14.74**
TARGETED (BETW. CENT.TY)	LINK	1	SHORT	28.6840	27.6620	36.5360	**24.29**
TARGETED (BETW. CENT.TY)	LINK	2	LONG	13.7340	13.1020	15.2360	**14.01**
TARGETED (BETW. CENT.TY)	LINK	2	SHORT	14.6260	14.4880	19.2000	**24.54**
TARGETED (BETW. CENT.TY)	LINK	4	LONG	8.1060	7.9000	9.7440	**18.92**
TARGETED (BETW. CENT.TY)	LINK	4	SHORT	8.5020	8.6200	12.0720	**29.57**
TARGETED (OUT-DEG. CENT.TY)	NODE	1	LONG	7.6000	12.6040	16.4520	**53.81**
TARGETED (OUT-DEG. CENT.TY)	NODE	1	SHORT	7.4880	11.7220	19.5420	**61.68**
TARGETED (OUT-DEG. CENT.TY)	NODE	2	LONG	4.5420	7.0260	8.9740	**49.39**
TARGETED (OUT-DEG. CENT.TY)	NODE	2	SHORT	4.5220	6.6280	10.5100	**56.97**
TARGETED (OUT-DEG. CENT.TY)	NODE	4	LONG	3.0260	4.2620	5.2940	**42.84**
TARGETED (OUT-DEG. CENT.TY)	NODE	4	SHORT	2.9860	4.0820	6.0340	**50.51**
TARGETED (OUT-DEG. CENT.TY)	LINK	1	LONG	51.8400	60.1520	67.4840	**23.18**
TARGETED (OUT-DEG. CENT.TY)	LINK	1	SHORT	46.2920	51.5620	69.9460	**33.82**
TARGETED (OUT-DEG. CENT.TY)	LINK	2	LONG	25.5140	29.2640	33.5300	**23.91**
TARGETED (OUT-DEG. CENT.TY)	LINK	2	SHORT	23.2680	26.1080	35.7220	**34.86**
TARGETED (OUT-DEG. CENT.TY)	LINK	4	LONG	13.1280	15.7520	18.6920	**29.77**
TARGETED (OUT-DEG. CENT.TY)	LINK	4	SHORT	12.1860	14.8800	21.4420	**43.17**
TARGETED (IN-DEG. CENT.TY)	NODE	1	LONG	7.8440	12.6920	16.3400	**52.00**
TARGETED (IN -DEG. CENT.TY)	NODE	1	SHORT	7.3720	11.8420	19.4540	**62.11**
TARGETED (IN -DEG. CENT.TY)	NODE	2	LONG	4.7020	7.1600	8.9280	**47.33**
TARGETED (IN -DEG. CENT.TY)	NODE	2	SHORT	4.4720	6.7080	10.5600	**57.65**
TARGETED (IN-DEG. CENT.TY)	NODE	4	LONG	3.1000	4.2940	5.2680	**41.15**
TARGETED (IN -DEG. CENT.TY)	NODE	4	SHORT	2.9840	4.1300	6.0500	**50.68**
TARGETED (IN -DEG. CENT.TY)	LINK	1	LONG	52.8280	59.9960	67.2340	**21.43**
TARGETED (IN -DEG. CENT.TY)	LINK	1	SHORT	43.5800	44.6640	57.5180	**24.23**

TARGETED (IN-DEG. CENT.TY)	LINK	2	LONG	25.4080	29.5280	33.2300	**23.54**
TARGETED (IN -DEG. CENT.TY)	LINK	2	SHORT	23.5800	24.4960	30.5360	**22.78**
TARGETED (IN -DEG. CENT.TY)	LINK	4	LONG	13.3340	15.9820	18.6160	**28.37**
TARGETED (IN -DEG. CENT.TY)	LINK	4	SHORT	12.850	13.814	17.642	**27.16**

5.3. Model validation

This section provides model validation. First, we note how resilience performances change in presence of short vs. long loops. The results show that long loops are less resilient than short loops, as proven by the higher percentage of destroyed loops observed on any network pattern. For instance, on Erdos-Renyii-like pattern, after a randomly selected node (link) is removed the percentage of long loops destroyed is 51.1% (18.7%) while that of short loops is 10.9% (3.4%). On small-world -like patterns, after two random nodes are removed, short (long) loops collapse after 10.9 (9.5) time instances. The same occurs in presence of targeted disruptions. For instance, on Erdos-Renyii-like pattern, after the node with the highest indegree centrality is removed, the percentage of long loops destroyed is 69.2% while that of short loops is 19.6%. These results run as expected. Compared to short loops, long loops involve a higher number of firms so resulting in a higher probability of being disrupted. Second, we note that CE networks are less resilient to high impact disruptions, as proven by the higher percentage of loops destroyed and the lower time to collapse. For example, on Erdos-Renyii -like patterns, after the removal of 1 vs. 4 random nodes (links), the percentage of disrupted long loops increases from 51.1% (18.7%) to 94.2% (53.1%). On the same network pattern, after the removal of 1 vs. 4 random nodes, the time to collapse of long (short) loops decreases from 17.3 (17.07) to 5.5 (5.5) time instances. As expected, similar trends are observed on the other network patterns. The higher the number of disruptions occurring within the network, the higher the probability that a higher number of loop structures collapse, the lessen the time before the entire network collapses. Finally, we test the consistency of our results by varying the network size. To this aim, we simulate the resilience of small CE networks ($N = 20$ and $\sigma = 0.2$). The results reported in Tables 4 and 6 confirm the above trends, including those discussed in Sections 5.1. and 5.2.

Additionally, we note that network size affects the resilience of CE networks. Table 5 (Table 7) reports the differences on the averaged values of the percentage of destroyed loops (time to collapse) for short and long loops, under random- and target- placed disruptions, in CE networks with respectively N = 30 and N = 20 firms. In the case of Erdos-Renyii -like patterns, network size positively affects resilience performance. On large networks, loop structures involve a higher number of firms so that number of loops each firm is involved into decreases. As a consequence, a given disruption will lead to the collapse of a lower number of loops and the CE network, as a whole, will resist for longer time before collapsing. The positive effect of network size on resilience is confirmed also on small-world -like structures. The higher the number of firms, the higher the number of small clusters within the network, the lower the number of loop structures formed within them, and finally the lower the impact of a given disruption. Differently, in the case of scale-free -like patterns, network size negatively affects resilience performance especially to target-placed disruptions. In such a case, the larger the network, the higher the number of loop structures formed by highly-connected firms, and thus the higher the number of loops destroyed by a target-placed disruption and the lower the time to collapse.

Table 4: *The percentage of resource loops destroyed in CE networks (N=20)*

Disruption Type	Disrupted element	Disruption Impact	Cycle	Scale-Free	Erdos-Renyii	Small-world	Diff. %
RANDOM	NODE	1	LONG	67,0003	66,3653	71,5539	**7,25**
RANDOM	NODE	1	SHORT	14,5708	14,6715	14,8254	**1,72**
RANDOM	NODE	2	LONG	89,1294	89,0822	91,7244	**2,88**
RANDOM	NODE	2	SHORT	28,5424	28,1164	28,0583	**1,70**
RANDOM	NODE	4	LONG	98,3885	98,2216	99,0689	**0,86**
RANDOM	NODE	4	SHORT	51,1675	52,3768	51,2124	**2,31**
RANDOM	LINK	1	LONG	15,0506	17,5138	17,5355	**14,17**
RANDOM	LINK	1	SHORT	3,5441	3,8903	3,7315	**8,90**
RANDOM	LINK	2	LONG	29,2425	32,2086	31,7176	**9,21**
RANDOM	LINK	2	SHORT	6,9189	7,7640	7,2113	**10,88**
RANDOM	LINK	4	LONG	49,3796	53,0188	53,7064	**8,06**
RANDOM	LINK	4	SHORT	13,2515	14,8454	14,3540	**10,74**
TARG-BETWEENESS	NODE	1	LONG	92,9231	90,3308	89,9188	**3,23**
TARG-BETWEENESS	NODE	1	SHORT	39,2717	33,5657	27,7963	**29,22**
TARG-BETWEENESS	NODE	2	LONG	99,2472	98,5377	98,4760	**0,78**
TARG-BETWEENESS	NODE	2	SHORT	63,3901	54,5484	45,9044	**27,58**

TARG-BETWEENESS	NODE	4	LONG	99,9780	99,9243	99,9313	**0,05**
TARG-BETWEENESS	NODE	4	SHORT	87,3743	79,7195	70,9686	**18,78**
TARG-BETWEENESS	LINK	1	LONG	14,3278	19,5239	21,0158	**31,82**
TARG-BETWEENESS	LINK	1	SHORT	5,9544	6,8777	6,1918	**13,43**
TARG-BETWEENESS	LINK	2	LONG	28,5309	39,2022	41,1961	**30,74**
TARG-BETWEENESS	LINK	2	SHORT	12,0141	13,5551	12,3810	**11,37**
TARG-BETWEENESS	LINK	4	LONG	54,9691	71,2423	75,3348	**27,03**
TARG-BETWEENESS	LINK	4	SHORT	23,2368	25,9195	23,0866	**10,93**
TARG-OUTDEGREE	NODE	1	LONG	86,6884	73,6771	70,6960	**18,45**
TARG-OUTDEGREE	NODE	1	SHORT	29,7867	21,4429	14,9754	**49,72**
TARG-OUTDEGREE	NODE	2	LONG	97,8221	92,7011	91,5241	**6,44**
TARG-OUTDEGREE	NODE	2	SHORT	53,0749	38,9712	29,0178	**45,33**
TARG-OUTDEGREE	NODE	4	LONG	99,9017	99,2773	99,2139	**0,69**
TARG-OUTDEGREE	NODE	4	SHORT	79,7317	64,9384	52,7282	**33,87**
TARG-OUTDEGREE	LINK	1	LONG	9,5015	10,0868	10,1788	**6,65**
TARG-OUTDEGREE	LINK	1	SHORT	3,4947	2,8434	2,4697	**29,33**
TARG-OUTDEGREE	LINK	2	LONG	19,6630	20,4929	20,4575	**4,05**
TARG-OUTDEGREE	LINK	2	SHORT	6,7225	6,1698	4,3093	**35,90**
TARG-OUTDEGREE	LINK	4	LONG	39,7180	41,3347	40,9469	**3,91**
TARG-OUTDEGREE	LINK	4	SHORT	13,6107	11,8076	8,4547	**37,88**
TARG-INDEGREE	NODE	1	LONG	86,9844	74,0153	70,2656	**19,22**
TARG-INDEGREE	NODE	1	SHORT	30,8971	21,7686	15,6253	**49,43**
TARG-INDEGREE	NODE	2	LONG	97,9090	92,9905	91,3482	**6,70**
TARG-INDEGREE	NODE	2	SHORT	54,0612	39,2441	30,2699	**44,01**
TARG-INDEGREE	NODE	4	LONG	99,9034	99,2512	99,1360	**0,77**
TARG-INDEGREE	NODE	4	SHORT	81,0689	63,3755	52,6439	**35,06**
TARG-INDEGREE	LINK	1	LONG	9,9115	10,1394	10,2987	**3,76**
TARG-INDEGREE	LINK	1	SHORT	6,7952	8,7540	7,2192	**22,38**
TARG-INDEGREE	LINK	2	LONG	19,9173	20,5146	19,9722	**2,91**
TARG-INDEGREE	LINK	2	SHORT	13,6439	15,0287	12,4164	**17,38**
TARG-INDEGREE	LINK	4	LONG	39,5563	41,0003	39,9701	**3,52**
TARG-INDEGREE	LINK	4	SHORT	24,7808	21,3424	16,1429	**34,86**

Table 5: *The averaged values of the percentage of destroyed short/long loops, under random- and target- placed disruptions, in CE networks with respectively M = 30 and M = 20 firms*

Disruption Type	**Cycle**		**M= 30**			**M=20**			**Diff. (%)**	
		Scale-Free	**Erdos-Renyii**	**Small-world**	**Scale-Free**	**Erdos-Renyii**	**Small-world**	**Scale-Free**	**Erdos-Renyii**	**Small-world**
Random	Long	46,9417	54,3860	59,7086	58,0318	59,4017	60,8845	**-23,63**	**-9,22**	**-1,97**
	Short	14,7372	15,0809	14,5537	19,6659	20,2774	19,8988	**-33,44**	**-34,46**	**-36,73**
Targeted	Long	61,0479	60,8118	56,1118	60,9696	60,7913	60,5489	**0,13**	**0,03**	**-7,91**
	Short	41,1753	26,3332	13,8022	34,9394	29,4374	24,0334	**15,14**	**-11,79**	**-74,13**

589 ***Table 6:*** *The time to collapse of CE networks (N=20)*

Disruption Type	Disrupted element	Disruption Impact	Cycle	Scale-Free	Erdos-Renyii	Small-world	Diff. %
RANDOM	NODE	1	LONG	13,67	12,918	13,27	**5,50**
RANDOM	NODE	1	SHORT	14,422	13,648	14,174	**5,37**
RANDOM	NODE	2	LONG	7,606	7,276	7,35	**4,34**
RANDOM	NODE	2	SHORT	8,046	7,536	7,83	**6,34**
RANDOM	NODE	4	LONG	4,586	4,372	4,446	**4,67**
RANDOM	NODE	4	SHORT	4,808	4,564	4,642	**5,07**
RANDOM	LINK	1	LONG	62,45	52,844	55,248	**15,38**
RANDOM	LINK	1	SHORT	60,934	51,466	55,278	**15,54**
RANDOM	LINK	2	LONG	32,314	27,324	28,826	**15,44**
RANDOM	LINK	2	SHORT	31,988	26,482	28,478	**17,21**
RANDOM	LINK	4	LONG	17,158	14,746	15,472	**14,06**
RANDOM	LINK	4	SHORT	16,9	14,316	15,284	**15,29**
TARG-BETWEENESS	NODE	1	LONG	6,83	6,7	7,296	**8,17**
TARG-BETWEENESS	NODE	1	SHORT	7,488	7,234	8,278	**12,61**
TARG-BETWEENESS	NODE	2	LONG	4,474	4,47	4,804	**6,95**
TARG-BETWEENESS	NODE	2	SHORT	4,704	4,674	5,318	**12,11**
TARG-BETWEENESS	NODE	4	LONG	3,07	3,134	3,338	**8,03**
TARG-BETWEENESS	NODE	4	SHORT	3,186	3,272	3,6	**11,50**
TARG-BETWEENESS	LINK	1	LONG	36,91	29,766	31,102	**19,36**
TARG-BETWEENESS	LINK	1	SHORT	39,434	32,092	35,176	**18,62**
TARG-BETWEENESS	LINK	2	LONG	18,566	14,98	15,736	**19,31**
TARG-BETWEENESS	LINK	2	SHORT	20,042	16,288	18,174	**18,73**
TARG-BETWEENESS	LINK	4	LONG	10,504	8,53	8,958	**18,79**
TARG-BETWEENESS	LINK	4	SHORT	11,25	9,514	10,408	**15,43**
TARG-OUTDEGREE	NODE	1	LONG	9,416	11,014	12,224	**22,97**
TARG-OUTDEGREE	NODE	1	SHORT	9,816	11,048	12,882	**23,80**
TARG-OUTDEGREE	NODE	2	LONG	5,472	6,296	6,91	**20,81**
TARG-OUTDEGREE	NODE	2	SHORT	5,672	6,328	7,258	**21,85**
TARG-OUTDEGREE	NODE	4	LONG	3,478	3,952	4,192	**17,03**
TARG-OUTDEGREE	NODE	4	SHORT	3,596	3,922	4,408	**18,42**
TARG-OUTDEGREE	LINK	1	LONG	66,128	59,136	62,864	**10,57**
TARG-OUTDEGREE	LINK	1	SHORT	60,784	53,206	59,556	**12,47**
TARG-OUTDEGREE	LINK	2	LONG	32,366	28,868	31,208	**10,81**
TARG-OUTDEGREE	LINK	2	SHORT	30,946	27,564	30,348	**10,93**
TARG-OUTDEGREE	LINK	4	LONG	16,636	15,21	16,22	**8,57**
TARG-OUTDEGREE	LINK	4	SHORT	16,526	14,996	16,418	**9,26**
TARG-INDEGREE	NODE	1	LONG	9,668	11,15	12,412	**22,11**
TARG-INDEGREE	NODE	1	SHORT	9,81	11,286	12,972	**24,38**
TARG-INDEGREE	NODE	2	LONG	5,564	6,344	7,002	**20,54**
TARG-INDEGREE	NODE	2	SHORT	5,696	6,456	7,282	**21,78**
TARG-INDEGREE	NODE	4	LONG	3,54	3,914	4,24	**16,51**
TARG-INDEGREE	NODE	4	SHORT	3,628	3,994	4,428	**18,07**
TARG-INDEGREE	LINK	1	LONG	65,938	58,72	62,924	**10,95**
TARG-INDEGREE	LINK	1	SHORT	56,912	47,798	51,492	**16,01**
TARG-INDEGREE	LINK	2	LONG	32,404	28,874	31,022	**10,89**
TARG-INDEGREE	LINK	2	SHORT	30,092	25,412	27,548	**15,55**

TARG-INDEGREE	LINK	4	LONG	16,578	14,932	15,98	**9,93**
TARG-INDEGREE	LINK	4	SHORT	16,568	14,164	15,688	**14,51**

Table 7: *The averaged values of the time to collapse of short/long loops, under random- and target-placed disruptions, in CE networks with respectively N = 30 and N = 20 firms*

Disruption Type	Cycle	M= 30			M=20			Diff. (%)		
		Scale-Free	Erdos-Renyii	Small-world	Scale-Free	Erdos-Renyii	Small-world	Scale-Free	Erdos-Renyii	Small-world
Random	Long	21,2200	21,2707	21,6633	22,9640	19,9133	20,7687	**-8,22**	**6,38**	**4,13**
	Short	21,0253	19,9320	24,2870	22,8497	19,6687	20,9477	**-8,68**	**1,32**	**13,75**
Targeted	Long	15,1589	17,7657	20,7970	19,3079	17,5550	18,8018	**-27,37**	**1,19**	**9,59**
	Short	14,2043	15,9501	21,9939	18,6750	16,6249	18,4019	**-31,47**	**-4,23**	**16,33**

6. Discussion and conclusions

CE network resilience is the system's ability to preserve CE functions while facing with a disruption. In this study, we argue that CE functions are accomplished by implemented CE strategies such as reuse, repair, remanufacture, and recycle. These lead to the creation of a set of short and long resource loops involving multiple companies, thus characterizing CE networks. Disruptions, affecting random/target companies and their mutual resource flows, can destroy the resource loops so threatening the ability of the network to perform CE functions. Therefore, designing resilient CE networks is an urgent need.

This study shows that the structural pattern of the CE network influences the capacity in preserving the attendant resource loops from collapse, under disruptions. Thus, it is a driver of CE network resilience. In particular, depending on the disruption, a given structural pattern exhibits different levels of resilience. In the case of random-placed disruptions, a *scale-free* -like pattern preserves more loop structures than a *small-world* -like one, while under target-placed disruptions, our results indicate that a *small-world* -like structure is more resilient because a limited number of resource loops is destroyed. A hierarchy-based structure is thus beneficial in the case of random adversity, whilst it remains extremely vulnerable to interruptions on firms with a high number of import and/or export channels. In the latter case, a small-world pattern is preferred to limit the cascading failure of resource loops.

Our results also indicate that network pattern affects the time to collapse i.e., how long CE networks resist to sequential disruptions before all the resource loops collapse. In this regard, we observed that resource loops in small-world patterns resist longer, than in scale-free and random -like ones, under the sequential removal of random and target firms/links. In such cases, small-world patterns are preferred as characterized by an uneven and decentralized distribution of resource loops, slowing down their collapse.

This study offers multiple contributions to the literature. First, it proposes a novel conceptualization of CE networks focusing on resource loops, distinguished into short and long loop structures. These are associated with the implementation of CE strategies and are viewed as enablers of the CE functions. Consistently, we also provide a definition of CE network resilience as the system's ability of "*absorbing disruptions by preserving resource loops from collapse*". In so doing, we inherently respond to the recent call by Awan (2020) asking for a comprehensive definition of CE resilience, a topic not well addressed in the literature. Furthermore, a novel determinant for CE network resilience is analysed referring to the structural pattern of CE network. While this feature has been investigated with regard to supply networks (Giannoccaoro and Ifthikar, 2022) and industrial symbiosis networks (Fraccascia et al., 2021), it lacks in the case of CE networks, even though it is shown that they can exhibit different complex network patterns (Wang et al. 2018; Xu et al. 2019). In this way, this study enriches the knowledge about the structural drivers of CE resilience i.e., size, interdependency, redundancy, and diversity (Fraccascia et al. 2017; Zhu and Ruth 2013; Chopra and Khanna 2014)

This study provides implications for managers and policymakers. Managers are suggested to designing CE networks with small-world -like structures since these are more resilient than scale-free and Erdos-Renyii -like structures, especially while facing with target-placed disruptions. They thus should foster the creation of small industrial clusters for example supporting symbiotic relationships among firms, and they should ensure the existence of "bridging ties" between the focal firms of each cluster. To preserve scale-free -like CE networks against target-placed disruptions, managers should prioritize their focus on the *anchor* firms since through them a given disruption determines the simultaneous collapse of all the loops they are involved into. In particular, given the high vulnerability of long loops, managers should reduce the dependency of the anchor firms on the other partners involved in long loops. Instead, they should foster the development of more short loops through supply and customer diversification (Gaustad et al., 2018; Bag et al., 2019).

To policymakers, useful guidelines for the design of resilient CE networks are derived from the results. First, they should be aware that CE networks with short loops absorb disruptions better than those with long loops, and hence they are suggested to develop incentives to encourage more customer-supplier loops for reuse, repair, refurbish, and remanufacture. In this regard, taxation-related policy measures such as tax reductions on repair services and second-hand goods distribution by social enterprises could be applied (Lechner et al. 2021). Furthermore, to support the creation of short loops for repair and remanufacture, policy makers should design multiple actions to directly regulate products' durability and reparability, and reduce the uncertainty and confusion still perceived by the actors operating on second-hand markets. A policy mix may simultaneously set minimum requirements on the lifetime of products and their subparts, legal measures as mandatory availability of spare parts for a minimum number of years, and easier access to information relevant for both service providers and consumers such as how to repair/remanufacture products and the quality of repaired products (Milios, 2018; Maitre-Ekern and Dalhammar 2016). Another fruitful action is fostering the adoption of public procurement policies through the introduction of resource efficiency standards, mandatory eco-design rules, and reward scores to second-hand and/or remanufactured products procurers. Second, based on the superior resilience proven by *small-world* -like network patterns, the links of *source* (high out-degree connectivity) and *end* (high in-degree connectivity) enterprises should be continuously monitored. In this regard, circular trading platforms can play a key role by increasing resource transparency across all stages of the product lifecycle, thus providing the basis for network visibility in times of disruptions (Hartley et al. 2020).

This study is not exempt from limitations. In our model, CE networks are described as sets of short and long loops developed from static inter-firm relationships. While this assumption is valid in the short-term, it fails in the long-term when firms tend to self-organize their relationships so as to pursuing both local (e.g., increasing resource efficiency and profit) and global interests (e.g., promoting a sustainable development). Borrowing from complex network theory (Goldstein, 1999), self-organization leads to the emergence of coherent structures, which in turn may affect the efficiency and resilience of CE networks. Extending the model to include dynamic relationships would allow us also capturing the evolution of short and long loop structures, and the adaptive capacity of CE networks while facing with disruptions. This refers to the dynamic facet of resilience (Massari and Giannoccaro 2021; Giannoccaro and Iftikhar, 2022), not investigated in this study. Furthermore, we modelled the CE network as an unweighted graph. Despite this is consistent with other studies investigating the resilience of ISNs (Wang et al. 2017; Wang et al. 2018; Zeng et al. 2013) and traditional SCs (see Choudhary et al. 2021; Pagano et al. 2019; Zhao et al. 2019 Kim et a., 2015), we acknowledge that a weighted directed graph could provide a more realistic approach to simulate CE networks (Chan and Janes 2023; Shan et al. 2023). We intend to address these aspects in the future.

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Declaration of interest

All the authors declare no conflicts of interest.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: