



Are circular innovations disruptive? An analysis of the role of inventor networks in the European semiconductor industry[☆]

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ABSTRACT

The expansion of advanced technologies is intensifying demand for energy, materials, and efficiency of production systems, with semiconductors exemplifying the tension between rapid technological progress and resource sustainability, and the development of circular innovations. Yet it remains unclear whether circular innovations in this sector tend to be genuinely disruptive. This study examines the disruptiveness of circular (vs. non-circular) innovations and analyses the role of inventor network structures. The empirical analysis relies on the patents of 299 European Semiconductor Equipment Manufacturing (SEM) companies retrieved from the ORBIS IP database for the period 2013–2022. First, we operationalize disruptiveness by adopting a citation-based measure to reveal whether subsequent inventions build upon or bypass a focal patent's prior art. Then, co-inventor networks are constructed, and inventor centrality and cohesion measures are aggregated to the patent level to link inventor network structure to disruptive outcomes over time. Our findings show that circular patents exhibit, on average, higher disruptiveness than non-circular patents, and that inventor network structures characterized by more peripheral and high local cohesive configurations align with disruptive circular outcomes. The effect of the network antecedents differs systematically between circular and non-circular innovations, indicating distinct pathways to disruption. The study contributes to the innovation literature by integrating a structural disruptiveness measure with inventor network analytics, offering one of the first patent-level comparisons of circular versus non-circular disruptiveness in the semiconductor industry, and by deriving implications for organizing collaboration portfolios and policy instruments that foster circular transitions.

1. Introduction

The rapid expansion of digital technologies has placed unprecedented demands on energy, materials, and production systems, particularly in high-tech manufacturing. As industries embark on a shift toward AI, automation, and advanced computing, the environmental and resource pressures of these technologies have come under scrutiny. This tension is particularly evident in the semiconductor industry, a foundational sector enabling advanced electronics, yet heavily reliant on scarce resources such as germanium, indium, and yttrium (O'Connor et al., 2016). With global e-waste reaching 62 million metric tons in 2022 (UNITAR, 2024) and semiconductor firms still operating largely within a non-circular production model, concerns over sustainability, resource dependency, and ecological degradation have become urgent

and systemic (Coad et al., 2021). Despite the sector's contributions to digital technologies, the environmental cost of its growth has raised pressing questions about how to combine innovation and sustainability.

Circularity has emerged as a promising framework to reconcile technological advancement with environmental responsibility. Circularity emphasizes keeping materials in use through strategies such as design for longevity, reuse, recycling, and remanufacturing (Circular Economy Action Plan, 2020). For high-tech and resource-intensive sectors like semiconductors, circular innovation holds particular promise, enabling reduced material throughput, enhanced resource efficiency, and more sustainable production-consumption loops (Kirchherr et al., 2017; Parte and Alberca, 2024). At the policy level, circularity has become central to the European Union's strategic agenda, embedded within the Green Deal and CE Action Plan to reduce import dependency

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and mitigate environmental impacts in sectors like electronics and ICT (Fitch-Roy et al., 2019; Ciani and Nardo, 2022).

Much of what is currently labeled as circular innovation remains oriented toward consolidating or reinforcing existing innovation trajectories, through efficiency improvements in production, enhanced material management processes, or design tweaks that reduce material intensity, without fundamentally reconfiguring inventive procedures, product architectures, or business models (Edmondson et al., 2019; De Angelis, 2024). However, some circular innovations can require novel reconfigurations of material choices, design logics, or system architectures, and thus align more closely with the notion of disruptive innovation. In Christensen's (1997) original formulation, disruptive innovations might initially underperform on mainstream criteria but introduce novel forms of value that eventually displace incumbent technologies and reshape dominant industrial trajectories (Christensen and Raynor, 2003; Si and Chen, 2020). Translated into the sustainability domain, disruption not only redefines market logics but also directly challenges the prevailing linear production systems, potentially accelerating transitions toward circularity (Blomsma et al., 2022; Yang, 2025).

Whether an innovation becomes disruptive is not solely a matter of its technical characteristics. Innovation is also a social and institutionally embedded process, shaped by collaborative routines, governance arrangements, and the positions of actors within networks. In this sense, the social dimensions of innovation refer to the relational, organizational, and institutional conditions through which knowledge is created, coordinated, legitimized, and diffused, including the transformation of social relations, socio-political capabilities, collective learning, and the social technologies that organize cooperation and value co-creation (Nelson and Sampat, 2001; Solano et al., 2025). These dimensions matter for disruption because the ability to develop novel technologies to challenge dominant trajectories depends not only on technical novelty but also on access to heterogeneous knowledge, departing from established routines, and coordination mechanisms required for alternative trajectories to emerge (Wang et al., 2017). This is especially salient within the context of circular innovation, which often requires the integration of diverse expertise, cross-domain collaboration, and new forms of coordination to challenge entrenched non-circular production systems (Giurca and Metz, 2018; Aza-Mengoa et al., 2025).

Despite these conceptual overlaps, we lack systematic evidence on whether, or to what extent, circular innovation is inherently disruptive. In particular, little is known about under which conditions circular innovations present disruptive characteristics and how these differ from non-circular innovations. Existing studies have mainly operationalized disruptiveness through patent-level technical attributes, such as novelty, diversity, and impact on other technologies, while paying limited attention to the social dimensions through which inventions are generated. Inventors are not only individual creators, but actors embedded in collaborative structures whose positions within their networks shape access to knowledge, exposure to redundancy, opportunities for recombination, and the ability to depart from dominant trajectories. The inventors' position within collaboration networks, whether peripheral, central, cohesive, or structurally diverse, may therefore influence whether inventions are positioned within and reinforcing existing innovation trajectories or becoming disruptive. In circular contexts, where heterogeneous expertise and sustained coordination are often required, these social dimensions may be even more consequential than for innovation within conventional settings. This unresolved tension motivates our research question: Are circular innovations more disruptive than non-circular innovations, and if so, how do the network antecedents of disruptive circular innovations differ from those of non-circular ones?

To address this question, we draw on the citation-based disruptiveness measure developed by Funk and Owen-Smith (2016) and its refinements (Zhang et al., 2024b; Yang, 2025), which capture whether subsequent inventions primarily displace or consolidate the knowledge

base upon which a focal patent builds. In contrast to approaches that approximate disruptiveness through proxies such as novelty or forward citation counts, this measure relies on tripartite citation patterns to identify whether later patents bypass or continue to co-cite/consolidate the focal patent's predecessors. Our empirical focus is on circular innovations, as proxied by patents, and whether they displace or consolidate prior knowledge. Additionally, we claim that disruptiveness does not arise solely from the technical content of patents but also results from the inventive process. Inventors carry knowledge and recombine their knowledge, generating novel knowledge; their structural positions in collaboration networks influence their exposure to heterogeneous perspectives, redundancy, or peripheral insights that may enable novel recombination (Lissoni and Ferrucci, 2019; Schillebeeckx et al., 2019). Because circular innovations often demand integration across diverse domains, sectors, and disciplines (Kuhlmann et al., 2022), they may emerge from specific network configurations. Thus, we extend the analysis to the inventor level and consider co-inventor networks over time. Analyzing patents of 299 European Semiconductor Equipment Manufacturing (SEM) companies in the period between 2013 and 2022, retrieved from the ORBIS IP database, we compute centrality and cohesion measures and aggregate them at the patent level to test whether particular network configurations are systematically associated with disruptive outcomes. This enables us to evaluate whether peripheral inventors, who are less tied to dominant networks or cohesive inventor groups, are more conducive to disruptive circular innovation.

Our contributions are threefold. First, we provide a systematic comparison of disruptiveness in circular and non-circular patents in semiconductors, shedding light on whether circular innovations are more disruptive than non-circular ones. Second, we integrate technical indicators of disruptiveness with inventor network structures, offering a novel perspective that links technological and social dimensions of innovation. Third, by examining the interaction between circular orientation and network position, we contribute to research on disruption in socio-technical transitions, demonstrating how sustainability aims intersect with network dynamics, including social dimensions, to shape disruptive outcomes. These findings offer practical implications for firms and policymakers seeking to accelerate the transition toward circular economies by fostering inventor collaborations and ecosystem configurations conducive to circularity.

The remainder of this paper is structured as follows. Section 2 reviews the literature on circularity and disruptive innovation in the semiconductor sector. Section 3 describes our data and methods, including the construction of the disruptiveness index and inventor network metrics. Section 4 presents empirical results. Section 5 discusses theoretical and policy implications, and Section 6 concludes.

2. Literature review

2.1. Semiconductor technologies, circular innovations, and technological disruptiveness

Circularity has become central to sustainability debates in resource-intensive sectors such as semiconductor manufacturing. In the semiconductor sector, there is often a stable yet paradoxical relationship between ongoing technological advancements and sustainable outcomes (Liu et al., 2023). Although advancements in semiconductor technologies, such as enhanced equipment functionality and energy efficiency, are believed to promote sustainability, these benefits are often counterbalanced by the growing consumption of electronics and their integration into diverse products, leading to more resource use (Lüthje, 2006). Circularity offers a pathway to reconcile these tensions by promoting material resilience, closed-loop processes, and minimized waste, thereby optimizing resource use and reducing environmental impact (Parte and Alberca, 2024). The circularity paradigm reorients design and operations toward longevity, reparability, remanufacturing, and recycling, intending to slow consumption and production loops and

enhance environmental quality, economic resilience, and social equity (Ellen MacArthur Foundation, 2013; Kirchherr et al., 2017).

While innovation is a key driver of resource efficiency and circularity, the literature still lacks a comprehensive understanding of how technologies addressing circularity contribute to sustainability at scale (Cainelli et al., 2020). At the technological level, circular innovations can be defined as invention-driven solutions that intentionally redesign how resources are sourced, used, and recovered to narrow consumption and production as well as extending product and component lifecycle via repair, refurbishment and reuse, by recovering used materials and energy to productive use, and regenerate by restoring natural and technical system capacity (Valero-Gil and Scarpellini, 2024). Conceptually, these technologies go beyond conventional eco-innovation: they target systemic shifts in production and consumption patterns, coordinate actors and incentives across value chains, and embed capabilities that actively enable circular flows (Geissdoerfer et al., 2017; Kirchherr et al., 2022; Portillo-Tarragona et al., 2022; Sehnem et al., 2022). The literature also suggests that circular innovations vary in the breadth of actors involved and their coordination demands. Some circular inventions mainly improve existing products, processes, or recovery practices, whereas others demand broader collaboration across heterogeneous actors, drawing on complementary knowledge and resources to share risks, costs, and implementation challenges (Rainville, 2021; Brown et al., 2020).

The debate on whether circular innovations need to be, or inherently are, disruptive is pivotal to understanding their transformative potential in the transition toward sustainable economic systems. Disruptive innovations, in the classical definition by Christensen (1997), displace incumbent market offerings and reshape industrial structures. In the context of circularity, disruption is not merely about product substitution but about fundamentally challenging and transforming the prevailing non-circular “take-make-use-dispose” model (Blomsma et al., 2022). Circular innovations are deemed disruptive when they shift socio-technical arrangements toward resource efficiency, waste reduction, and regenerative design (Webster, 2017). As Blomsma et al. (2022) argue, circular disruption entails a systemic transformation that rapidly reorients industries around circular principles, reducing structural waste and redefining value creation.

A key technological dimension of circular disruption is the development and adoption of alternative material extraction processes and renewable materials. However, such shifts often involve trade-offs in performance or process compatibility. For example, in the semiconductor industry, bio-metallurgy, where microorganisms such as bacteria and fungi recover valuable metals from electronic waste through bioleaching or biosorption, often underperforms compared to conventional extraction methods in terms of efficiency and scalability during its early stages, but it supports resource circularity and reduces the environmental burden (Smith and Behdad, 2025). These limitations mirror a well-known trait of disruptive technologies: initial underperformance on established technical metrics but strong alignment with emerging socio-environmental norms (Guo et al., 2018).

2.2. Measuring disruptiveness: Characteristics of disruptive innovation

Key features of disruptive innovations are their departure from established knowledge for novelty, their delayed but growing technological impact, and their cross-domain technological integration. Technological disruption is often closely associated with the concept of technological breakthroughs, as both entail sudden shifts that alter the prevailing status quo (Bower and Christensen, 1995; Yang, 2025). Measuring this transformative innovation requires an examination of both ex-ante novelty and ex-post impact of a given innovation (Yang, 2025). Importantly, disruptiveness should not be treated as synonymous with radicality but rather embodies breakthrough knowledge that diverges significantly from a dominant design (Petrucelli et al., 2015).

Early studies of technological disruption often relied on forward

citation counts as indicators of a patent's significance. Forward citations were treated as a proxy for technological impact, based on the assumption that highly cited patents shape subsequent innovations more strongly (Higham et al., 2021). However, citation counts collapse heterogeneous motivations to cite into a single metric, capturing visibility rather than the nature of impact exerted (Zhu and Li, 2025). As a result, high citation does not necessarily signal disruptiveness: a patent may be influential because it consolidates a trajectory rather than displaces it. To address this limitation, scholars turned to measures of novelty, operationalized as the degree to which an invention departs from established knowledge bases.

Novelty captures ex-ante distinctiveness, often using unusual combinations of technological classes (Fleming and Sorenson, 2001) or semantic distance in patent texts (Fontana et al., 2020; Sun et al., 2021). Novel inventions may reflect conceptual leaps, but novelty alone is insufficient: many novel ideas fail to diffuse, remaining isolated or irrelevant to future developments (Arthur, 2007; Yang, 2025). This recognition led to frameworks that combine novelty with impact, producing more dynamic views of breakthrough innovation (Esposito, 2023). These measures acknowledge that true disruption requires not only deviation from the past but also subsequent uptake by future technologies.

A key conceptual advance came with the Consolidation–Disruption (CD) index (Funk and Owen-Smith, 2016). The CD index reframes disruptiveness as a relational property, not in terms of how many times a patent is cited, nor how novel its content is, but whether it redirects attention away from its predecessors. If forward citations reference the focal patent without co-citing its predecessors, the lineage is destabilized (disruption). If they co-cite both focal and predecessors, the lineage is reinforced (consolidation). Disruptiveness is therefore observed in the pattern of knowledge rerouting within local citation networks. This perspective distinguishes disruption from simple impact: a patent can be highly cited yet consolidating or modestly cited yet profoundly disruptive.

The CD index has been validated and applied across diverse domains, demonstrating its flexibility and robustness to variations in citation practices (Yang, 2025), from citation analysis of journals and patents to innovations across different technological domains and industries (Horen et al., 2021; Yang, 2025). Overall, this index provides a systematic, network-structural read on how a work displaces predecessors.

2.3. Inventor networks in disruptive circular innovation

The extant literature increasingly recognizes that circular transitions challenge not just technologies and business models but entire socio-technical arrangements (Geels, 2004; Markard et al., 2012). In addition to the socio-technical dimension, inventor networks play a critical role in enabling such systemic transformations. Collaborations could be operationalized by co-inventor networks, which are made up of links between inventors who have worked together on at least one patented innovation (Abbasiharofteh et al., 2023). These networks are beneficial because co-invention brings inventors together and enables the possibility of new knowledge recombination (Kogut, 2000; Abbasiharofteh et al., 2023). The majority of co-investor partnerships are limited to a small number of patents, whereas new partnerships provide fresh knowledge combinations (Fritsch and Kudic, 2021).

Disruptive technological breakthroughs present combinations that have rarely been made before or are entirely new (Kim et al., 2016; Wang et al., 2017), blending distinct knowledge domains into new knowledge (Wagner et al., 2019; Fontana et al., 2020). Such innovations are created in collaboration (Inkpen, 1996; Abbasiharofteh et al., 2023). Disruptive innovations often originate from marginal actors whose distance from mainstream knowledge enables them to recombine ideas across disparate domains (Fleming, 2007; Capponi et al., 2022). In contrast to conventional wisdom, breakthrough innovations often stem from loosely connected or structurally open networks (Burt, 2004).

Thus, we hypothesize:

H1. Innovations developed by inventors located at the periphery of collaboration networks are more likely to display disruptiveness.

Disruptive circular innovations often require integrating interdisciplinary knowledge, for example, linking device physicists with recycling experts or fab engineers with sustainability designers (Schimpf et al., 2024). Such innovation processes bring together heterogeneous actors who self-organize, foster inter-sectoral collaboration, and develop new forms of knowledge production and exchange (Giurca and Metz, 2018). These new constellations of expertise signal a structural break from existing collaboration patterns, reflecting broader changes in the innovation dynamics. As circular solutions become increasingly complex and cross-sectoral, disruptions become evident not just in the technologies themselves but in the configuration and evolution of inventor networks (Liu et al., 2023). In this sense, whether circular innovation reinforces existing technological trajectories or becomes disruptive may depend on how actors are configured within the innovation process. Because the knowledge recombination required for circular innovation is often complex and heterogeneous, the relevant actor configurations may also extend beyond dominant or established actor types (Bocken and Ritala, 2021). Structural shifts, such as the formation of new collaborations, changes in centrality, and the emergence of previously disconnected knowledge domains, suggest that the disruptiveness of circular innovations is as much about network transformation as it is about technological novelty (Kuhlmann et al., 2022). Thus, we hypothesize:

H1a. In circular innovation contexts, H1 is amplified, such that disruptive circular patents are more likely to originate from peripheral teams than from those embedded in the structural core.

According to the innovation literature, high local cohesion can constrain the emergence of disruptive innovation by narrowing perspectives and reinforcing socially proximate forms of interaction within a technological paradigm (Dosi, 1982). Breakthrough innovations are often more likely to arise outside habitual patterns of collaboration, where weak ties, structural holes, and unconventional relationships provide access to non-redundant knowledge and novel combinations of ideas (Granovetter, 1973; Innocenti et al., 2021). By contrast, cohesion in the absence of diversity tends to reproduce redundancy and conformity pressures, thereby limiting the heterogeneous knowledge recombination required for disruptive outcomes (Wiarda et al., 2024). Excessive overlap in ties may also generate coordination costs and cognitive overload, which can further discourage departures from established technological paradigms (Tubiana et al., 2021). At the same time, the literature highlights the importance of boundary-spanning partnerships across domains and sectors, as actors with dissimilar yet complementary knowledge bases expand the search space and open new pathways for recombination (Markus et al., 2024). Establishing ties with cognitively distant actors is therefore particularly important for disruptive innovation and the acquisition of novel knowledge (Innocenti et al., 2021). Building on this reasoning, we hypothesize:

H2. Innovations developed by inventors embedded in highly cohesive cognitive neighborhoods are less likely to be disruptive.

Mission-oriented innovations like circular innovations present a distinct case. Circular innovation demands integration of material science, design, and sustainability knowledge, which often resides across distant knowledge domains. Yet effective knowledge recombination does not depend on a diverse set of actors alone; it also requires a sufficiently broad set of actors and relational conditions that support trust, efficient knowledge transfer, and the development of a shared technical language (Kuhlmann et al., 2022). Cohesive but open clusters become critical enablers. Cohesive subgroups are subsets of actors among whom there are relatively strong, direct, intense, frequent, or positive ties (Innocenti et al., 2021). Evidence from circular innovations shows that deep, frequent, and trusted interactions among partners foster trust,

reduce opportunism, and support the “learning-by-interacting” processes that are particularly crucial for complex eco-process innovations (Tubiana et al., 2021). Likewise, mission-oriented approaches are explicitly designed to align heterogeneous stakeholders around systemic sustainability goals, forming “mission-driven clusters” that coordinate diverse expertise toward transformative change (Wiarda et al., 2024). This aligns with emerging arguments that disruptive circular innovations exhibit unique structural signatures, marked by local cohesion and mission-driven clustering (Mies and Gold, 2021). Thus, we hypothesize:

H2a. In circular innovation contexts, where heterogeneous expertise and sustained collaboration are essential for integrating material, design, and sustainability knowledge, cohesive inventor teams are likely to generate disruptive outcomes.

3. Methodology

3.1. Research setting

We analyze the disruptiveness related to the circular innovation in the European Semiconductor Equipment Manufacturers (SEMs), using patents as the unit of analysis. SEMs are pivotal, as they develop the automated machinery essential for semiconductor manufacturing processes, including manufacturing, testing, and packaging (Ciani and Nardo, 2022). European-based SEMs are among the top global input suppliers for semiconductor production (De Jong, 2020). We specifically focus on the innovation dynamics within the SEMs located in Europe, not only due to their critical role in the supply chain, but also because of the intense political debates surrounding environmental sustainability in the region (European Commission, 2025; Ciani and Nardo, 2022). The European Union's active engagement in sustainability discussions makes it a significant area of study, particularly to understand how these debates influence innovation strategies within the semiconductor sector.

3.2. Dataset

We identified European SEMs by employing relevant industry classifications, NACE, and specific NAICS codes (e.g., NACE 2611 – “Manufacturers of Electronic Components and Equipment”), in conjunction with targeted keywords¹ (e.g., “Semiconductor” AND (“Machinery” OR “Equipment”)), search in the company description and history, main and secondary activities, product and services, and trade description.²

We identify a total of 854 SEM companies located in Europe, of which 299 companies (35%) exhibit patenting activities during the period between 2013 and 2022. We constructed our dataset by extracting all the patents granted to these firms for the considered period using the ORBIS IP database (Bureau Van Dijk). This database consolidates and harmonizes global patent data from multiple sources, offering comprehensive information such as inventor names, affiliated organizations, International Patent Classification (IPC), and Cooperative Patent Classification (CPC³) codes, as well as patent grant dates. Following the collection of all patents by SEMs, we undertook essential cleaning steps to remove duplications, identify patent families and unique

¹ The keywords are based on the EU JRC Classification (Ciani and Nardo, 2022), as well as based on the semiconductor manufacturing handbook (Wolf and Tauber, 1986).

² We acknowledge and express our gratitude to the researchers at the EU Joint Research Centre (JRC) in Ispra for their valuable time for verifying the list of Semiconductor Equipment Manufacturers (SEMs) used in our analysis and for reviewing the industry classifications codes applied in the identification process.

³ The Cooperative Patent Classification (CPC), jointly developed by the EPO and USPTO, builds on the IPC system to provide more precise patent categorization (Leydesdorff et al., 2017).

patents, standardize dates and classification codes, and normalize the names of inventors and patent owners. These processes are necessary to ensure data accuracy and facilitate reliable analysis by rectifying inconsistencies and standardizing entries across diverse sources.

Further, we develop a novel methodological approach to systematically identify circular innovations within patent data, recognizing that circular innovations represent a specialized subset within the broader category of environmentally sustainable technologies. To construct the initial pool of circular patents, we adopt the enhanced classification framework proposed by Portillo-Tarragona et al. (2022), which refines traditional green patent classifications by incorporating a broader interpretation of circularity grounded in environmental and systemic innovation perspectives. This framework expands the scope of conventional approaches, often limited to waste management, by including patents, identified using a new set of IPC codes, that facilitate resource decoupling, sustainable production, and waste valorization, all of which are essential for enabling circular transitions.

Despite these advancements, the framework maintains certain limitations, particularly its exclusive reliance on IPC classifications at the main code level, which limits the granularity and precision necessary to capture the diverse technological context of circular innovations. To address this issue, we refine the methodology by incorporating IPC codes at both main and sublevel, aligning with recent advancements in patent analysis (Block et al., 2024; Valero-Gil and Scarpellini, 2024). Our approach identifies patents not solely based on their environmental relevance but also based on their functional alignment with core circularity objectives, including waste management, reuse, recycling, remanufacturing, and energy conservation. For instance, we explicitly include IPC codes such as B29B7/66 (“restoring or recycling materials”), which directly relates to extending product lifecycles—a fundamental principle of circularity.

Building on this refined pool, we implement a targeted, second-level classification approach inspired by Giglio et al. (2021), who developed a structured framework using the intersection of IPC and CPC codes to identify domain-specific patent clusters with high thematic relevance in the aircraft and aviation sectors. We adapt and develop it to circularity in the context of the semiconductor industry, moving beyond general green and eco-innovation classifications. Specifically, we select IPC and CPC codes at both main and subclass levels that explicitly align with circularity principles. Then, to enhance precision, we adopt the dual classification strategy, retaining only those patents classified under the same circularity-relevant subclasses in both IPC and CPC coding systems. For example, a patent is classified as circular if it is coded simultaneously under IPC H01M8/008 (“recycling of electronic cells”) and under CPC Y02W30/84 (“recycling of electronic cells”), ensuring thematic consistency and reducing potential biases arising from examiners' inconsistencies or system-level discrepancies. This approach mitigates the common limitation in prior studies that rely on single-system classifications at higher aggregation levels, which can result in unfocused patent pools. To ensure the internal robustness of our classification strategy, we implemented a complementary machine learning-based validation using a domain-adapted transformer model. Specifically, we employed the Patent-specific BERT (Bidirectional Encoder Representations from Transformers) Model (“anferico/bert-for-patents”), fine-tuned on the textual content (title and abstract) of patents (Vowinkel and Hähnke, 2023), labeled as circular or non-circular according to our IPC–CPC rule-based taxonomy. The model's performance and accuracy are optimal with an F1 score of 0.839. This additional step allowed us to assess the internal consistency of our coding scheme and to identify potentially misclassified patents (false positives or false negatives). The model's predictions were highly consistent with our dual IPC–CPC tags, with an agreement rate of around 93%, supporting the validity of our classification (see Appendix A1 for further details).

Our methodology explicitly focuses on circularity, identifying

patents that directly advance circular transitions within environmentally beneficial patents.⁴ This refinement responds to recent calls for rigorous mapping of circular innovation (Valero-Gil and Scarpellini, 2024), addressing the concern of conflating circular innovations with broader eco-innovations. Fig. 1 shows how the dual tagging mechanism is used to identify the circular patents.

3.3. Description of variables

3.3.1. Dependent variable: Disruptiveness index (DI)

The dependent variable is the disruptiveness of patents, which captures the extent to which a focal invention reshapes subsequent technological trajectories by displacing reliance on prior knowledge. Following Funk and Owen-Smith (2016) and subsequent refinements like construction bias (including the neutral citation path) and by estimating models that explicitly control for citation counts, and team size (Zhang et al., 2024b; Yang, 2025), we construct the disruptiveness index based on the citation structure surrounding each patent.

Consistent with the original tripartite formulation, the measure does not require observing citations to the patents that cite the focal patent. Instead, it is based on three elements: (i) the focal patent's backward-cited predecessors, (ii) the focal patent itself, and (iii) later patents observed within the citation window that cite the focal patent and/or at least one of its predecessors. For each focal patent, we therefore identify the set of subsequent patents falling into this citation neighborhood and classify them as follows:

- Disruptive: forward citation cites the focal only, bypassing its predecessors.
- Consolidating: forward citation cites both the focal and at least one predecessor.
- Neutral: forward citation cites only predecessors, not the focal.

Then, we compute the index⁵ as:

$$DI = \frac{N_{F,i} - N_{B,i}}{N_{F,i} + N_{B,i} + N_{R,i}}$$

Where $N_{F,i}$ is the number of disruptive forward citations, $N_{B,i}$ the consolidating citations, and $N_{R,i}$ the neutral citations. The index ranges from -1 (fully consolidating) to $+1$ (fully disruptive).

3.3.2. Independent variables: Inventor network characteristics

To capture the structural positions of inventors, we refer to co-inventor networks over time using patent data. Basically, we construct co-inventor networks using a three-year sliding window approach (Zhang et al., 2024a). For each target year t , we build a co-inventor network from patents granted in the preceding three years ($t - 3, t - 2$,

⁴ **Example of Patent:** ID- DE102011082187B4; Abstract- “The method involves realizing the comminution process subjected to the battery (20) containing lithium hexafluorophosphate, by using a mechanical tool. The comminution process is performed at an environmental fluid (10) containing alkaline earth metal surrounding the battery. The alkaline earth metal is selected from calcium or magnesium. The environmental fluid is an aqueous solution. The comminution process is a shredder process. The battery components are filtered or dried by the comminution process of the battery. An independent claim is included for a device for performing comminution of a battery containing lithium hexafluorophosphate.”; IPC and CPC Codes- H01M10/54 & Y02W30/84 (Reuse, recycling or recovery technologies)

⁵ An absence of direct forward citations to the focal patent does not, by itself, imply a disruptiveness score of zero, since subsequent patents may still cite the focal patent's predecessors and thus enter the neutral citation path. The disruptiveness index is considered undefined only when no subsequent patent within the observation window cites either the focal patent or any of its predecessors. These observations are therefore excluded from the estimation sample rather than treated as meaningful zero outcomes.

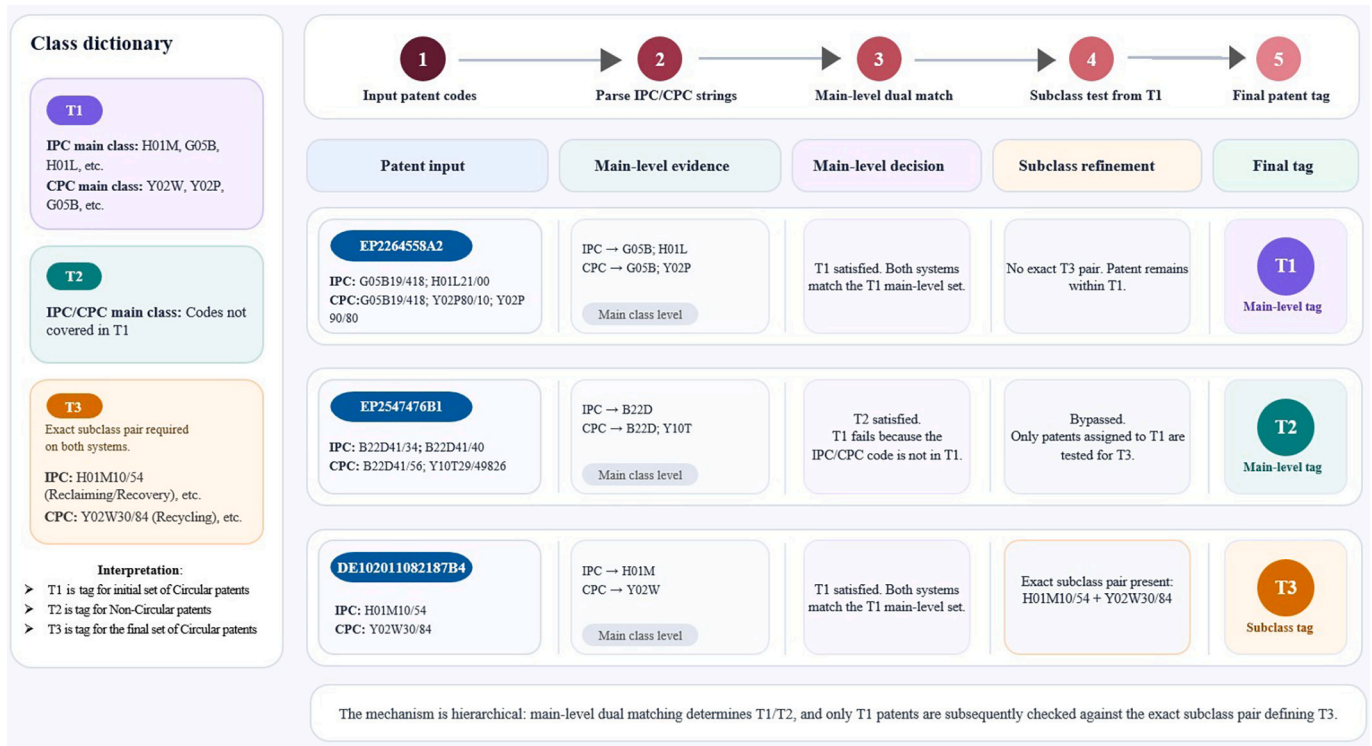


Fig. 1. Illustrative example of the dual tagging mechanism (actual patent examples)

Note: The dual classification strategy retains only those patents classified under the same circularity-relevant subclasses in both IPC and CPC coding systems. The comparison reflects circular patents (T3) versus non-circular patents (patents that are not strictly circular (excluded patents in T1) + and all other patents (in T2) under the CE-focused definition, rather than circular versus purely linear inventions.

$t - 1$). For example, patents granted in 2016–2018 form the network to assess an inventor's patent disruptiveness in 2019. This design ensures that network metrics are measured before the disruptive outcomes occur, thereby reducing simultaneity concerns and allowing us to measure the role of inventor network position ex-ante. In each look-back window, nodes represent inventors, and edges are created between any two inventors listed on the same patent. Edge weights reflect the number of joint patents filed between a given inventor pair within that period, thereby capturing collaboration intensity.

From these networks, we compute several network measures⁶ that capture different dimensions of an inventor's position and role in networks; then these metrics are aggregated to the focal patent level across all inventors listed on a patent team.

Inventor knowledge brokerage (INV_KnowBrok): It measures the extent to which inventors act as brokers connecting otherwise unlinked groups. Patents involving inventors with high betweenness centrality may benefit from access to structurally diverse information, enabling the recombination of distant knowledge domains, a key condition for disruptive breakthroughs (Burt, 2004; Forti et al., 2013).

Inventor influence (INV_Infl): Using the eigenvector centrality, we capture whether inventors are connected to other influential actors. Such positions enhance visibility and legitimacy within the network (Bonacich, 1987; Buenstorf and Costa, 2018). In the context of disruptive innovation, eigenvector centrality may allow unconventional ideas to diffuse more broadly, especially when peripheral inventors connect to influential clusters (Schillebeeckx et al., 2019).

Inventor Local Cohesiveness (INV_LocCohe): We use the clustering coefficient to capture local cohesiveness: a high clustering

coefficient means that an inventor's collaborators also collaborate with each other, forming a tightly knit neighborhood, whereas a low clustering coefficient suggests that the inventor connects otherwise unconnected collaborators (Hur and Oh, 2021). While cohesion fosters trust and ease of coordination, it also reproduces redundancy and conformity pressures, which can constrain the emergence of disruptive ideas (Granovetter, 1973; Uzzi and Spiro, 2005).

Inventor structural embeddedness (INV_StrEmb): Structural Embeddedness is measured using the k-core number. K-core number indicates the maximum k such that the inventor belongs to a k -core, i.e. a subgraph where every inventor has at least k links (Innocenti et al., 2021). High k -core positions are strongly aligned with dominant knowledge flows, whereas peripheral actors at lower k -core levels are freer to experiment outside established trajectories (Fleming, 2007).

3.3.3. Moderating variable: Circular patents

To test whether the relationship between network structure and disruptive inventions differs in the context of circular and non-circular innovation, we include a binary indicator that takes the value equal to 1 if the patent is classified as a circular patent, and 0 otherwise.

3.3.4. Control variables: Technical characteristics

We control for a set of patent-level technical characteristics. Specifically:

Technological novelty (TNov): Technological novelty, characterized by the introduction of significantly distinct technologies, concepts, processes, or products within a domain, plays a crucial role in driving novel innovations that disrupt existing paradigms and confer competitive advantages, thereby facilitating firm growth and development (Petrizzelli et al., 2015). We measure the extent of similarity of patents based on two methods: Cosine Similarity and Jaccard Similarity, and then take the average similarity and subtract it from 1 to obtain the relative novelty of a patent (Fontana et al., 2020).

⁶ All network metrics are computed using the NetworkX library in Python to ensure scalability and computational precision across the full dataset and are standardized as z-scores to allow comparability.

For each patent i , we calculate the Cosine and Jaccard similarities with every other patent j , where $i \neq j$, for both abstracts and claims.

$$\text{Cosine Similarity}_{ij} = \frac{A_i \bullet A_j}{\|A_i\| \|A_j\|} + \frac{C_i \bullet C_j}{\|C_i\| \|C_j\|}.$$

$$\text{Jaccard Similarity}_{ij} = \frac{|A_i \cap A_j|}{|A_i \cup A_j|} + \frac{|C_i \cap C_j|}{|C_i \cup C_j|}$$

Where A represents the vectorized representation of the patent abstract, C represents the vectorized representation of the patent claims, t is the grant year of patent i , $N_{<t}$ is the set of patent j such that $j_t \leq i_t$, $|N_{<t}|$ is the total number of patents in the set.

For each patent i , we compute the average of the Cosine and Jaccard similarities across all other patents and subtract it by 1 to obtain the Technological Novelty index.

$$TNov_i = 1 - \frac{1}{2|N_{<t}|} \sum_{j=1}^{|N_{<t}|} \text{Cosine Similarity}_{ij} + \text{Jaccard Similarity}_{ij}$$

Technological impact (TImp): Patents that garner a substantial number of citations are considered to exert significant impact on future technologies, highlighting the importance of the technologies they encompass (Nemet and Johnson, 2012; Higham et al., 2021). Furthermore, the inclusion of both direct and indirect citations is critical in assessing a patent's broader impact, especially in the realm of disruptive innovation, where such innovations often catalyze industry-wide transformations and inspire further research (Corredoira and Banerjee, 2015).

We calculate the total forward citations per year for all the present generations received by a patent and add them together to obtain the technological impact of a patent.

$$TImp = \sum_{k=1}^n \frac{\alpha^{k-1} FC_{i,k}}{Y_{i,k}}$$

Where, $FC_{i,k}$ represents total number of k^{th} generation citations received by patent i , $Y_{i,k}$ represents the number of years since the patent i was granted until the average grant year of the k^{th} generation citing patents, α is the attenuation factor to diminish the influence of further generations⁷, n is the total number of generations considered.

Technological diversity (TDiv): Technology diversity serves as a crucial indicator of disruptive technology by highlighting its potential applicability across various fields (Song et al., 2017; Fusillo, 2023). A technology with high diversity demonstrates a greater likelihood of generating a broader market impact and achieving significant penetration across multiple sectors.

We use Shannon's Diversity Index to calculate Technological Diversity. For each patent, we calculate the proportion of each IPC/CPC code over the total IPC/CPC codes present in the patent (De Noni et al., 2018; Zhu et al., 2022). This is done by dividing the frequency of each IPC/CPC code by the total number IPC/CPC codes.

$$TDiv = - \sum_{x=1}^N (p_x * \ln p_x)$$

where p_x is the proportion of the x^{th} IPC/CPC code in the specific patent, and N is the total number of different IPC/CPC codes.

These indices capture the inherent technical quality of patents and

mitigate concerns that disruptiveness is merely reflecting citation intensity or technological scope.

Inventor team size (ITeamSize): We also control for team size, measured by the number of inventors listed on a patent, as the larger the inventor team size, the higher the potential disruptiveness of a patent.

Table 1 summarizes the variables used in the empirical models and their operationalization.

3.4. Empirical analyses

3.4.1. Descriptive analysis

Table 2 presents descriptive statistics of the variables used in the empirical analyses.

Since the distribution of our disruptiveness index deviates from normality, as confirmed by Kolmogorov–Smirnov, Anderson–Darling, and D'Agostino tests, we apply the Mann–Whitney U test, a non-parametric alternative suited for skewed data, to test for the differences between the circular and non-circular patents. We implement the test for individual years to assess whether the relative disruptiveness of circular innovations changes over time. The results consistently show that circular patents exhibit significantly higher disruptiveness scores than non-circular patents across the majority of years, providing initial support for the assumption that circular innovations tend to be more disruptive to established technological trajectories.

Table 3 and Fig. 2 present the distributional assessment of the disruptive index across circular and non-circular patents (respectively, CI and non-CI), combining graphical and statistical diagnostics. The violin and kernel density estimation (KDE) plots reveal marked departures from normality, with both groups exhibiting pronounced peaks around zero and heavy tails. Non-circular patents show a sharper multi-modal distribution with wider dispersion and more extreme values, suggesting the presence of substantial heterogeneity and potential outliers. In contrast, circular patents display a relatively more compact central distribution, though still with evident asymmetry and tail heaviness. These visual impressions are corroborated by formal normality tests. The Kolmogorov–Smirnov test values are 0.2822 ($p < 0.001$) for non-CI and 0.2396 ($p < 0.001$) for CI, both rejecting the null of normality. Similarly, the D'Agostino test statistics are 291.99 ($p < 0.001$) and 539.56 ($p < 0.001$), respectively, again strongly indicating deviation from Gaussian assumptions. Finally, the Anderson–Darling statistics of 4310.49 for non-CI and 849.07 for CI further underscore significant non-normality at the 0.1% level. Taken together, these findings highlight the non-normal and multi-modal nature of the distributions, thereby indicating the use of non-parametric methods in regression analyses of disruptiveness for circular innovations.

Table 4 reports the results of the temporal Mann–Whitney U tests comparing the disruptive index of circular and non-circular patents from 2013 to 2022. In 2013, no significant difference was observed between the two categories ($p = 0.1298$), suggesting that circular patents did not yet exhibit a distinctive disruptiveness advantage. However, from 2014 onwards, circular patents consistently outperformed non-circular ones, with the exception of a marginal case in 2014 ($p = 0.0552$). In subsequent years, the differences became statistically significant at the 5% level and often at the 0.1% level, indicating a persistent and robust superiority of circular patents in terms of disruptiveness. The mean disruptive index for circular patents remained higher across all years, with particularly strong gaps observed between 2015 and 2019. Even in the later period (2020–2022), when overall average disruptiveness declined for both categories, circular patents continued to show significantly higher disruptiveness than their non-circular counterparts. These findings suggest that circular innovations not only maintained but consolidated their relative disruptive edge over time, reinforcing their strategic importance in the innovation landscape.

The correlation matrix in Table 5 shows that most of the variables used in the selection regression model do not present multicollinearity concerns, as the coefficients are below 0.5. However, the correlation

⁷ In this study, we employed a linear regression model to systematically determine the optimal value of alpha. The variable α acts as a scaling factor in our regression model, where the dependent variable, Patent Valuation, represents the Patent value influenced by these forward citations. The optimal alpha value, demonstrating the highest predictive accuracy and generalizability, is reported in Appendix A3.

Table 1
Summary of the variables.

Variable Name	Abbreviation	Type	Definition	Measurement	Source
Disruptiveness Index	DI	Dependent Variable	This variable measures the extent to which a focal invention reshapes subsequent technological trajectories by displacing reliance on prior knowledge.	This variable is based on the citation structure surrounding each patent. For each focal patent, we identify its backward citations (predecessors) and its forward citations (subsequent patents citing the focal one). Each forward citation is then classified according to whether it also cites the predecessors of the focal patent: Disruptive: forward citation cites the focal only, bypassing its predecessors. Consolidating: forward citation cites both the focal and at least one predecessor. Neutral: forward citation cites only predecessors, not the focal.	Funk and Owen-Smith, 2016 ; Zhang et al., 2024b ; Yang, 2025
Inventor Knowledge Brokerage	INV_KnowBrok	Independent Variable	This variable measures the extent to which inventors act as brokers connecting otherwise unlinked groups.	This variable is based on the betweenness centrality measuring how frequently an inventor lies on the shortest paths between other pairs of inventors.	Burt, 2004 ; Forti et al., 2013
Inventor Influence	INV_Infl	Independent Variable	This variable measures whether inventors are connected to other influential actors. Such positions enhance visibility and legitimacy within the network.	This variable is based on eigenvector centrality, which assesses the extent to which an inventor is connected to other well-connected or influential inventors within the co-inventor network. It captures not only the number of inventor's links but also the quality and prominence of their connections.	Buenstorf and Costa, 2018 ; Schillebeeckx et al., 2019
Inventor Local Cohesion	INV_LocCohe	Independent Variable	This variable measures the local cohesiveness, such that an inventor's collaborators also collaborate with each other, forming a tightly knit neighborhood.	This variable is based on clustering coefficient, measuring the ratio of existing links among an inventor's collaborators to the total number of possible links among them.	Hur and Oh, 2021 ; Innocenti et al., 2021
Inventor Structural Embeddedness	INV_StrEmb	Independent Variable	This variable measures the extent to which an inventor is deeply integrated into the dense core of the co-inventor network, rather than occupying a peripheral or loosely connected position.	This variable is based on the k-core number, mathematically it represents the largest value of k for which the inventor is part of a k-core, a subgraph in which every inventor maintains at least k connections with other members of that subgraph.	Innocenti et al., 2021 ; Fleming, 2007
Circular Patent	CP	Moderating Variable	This variable captures whether an invention is classified as a circular or a non-circular invention	This is a dummy variable which takes the value of 1 if the patent is classified as a circular patent and 0 otherwise.	Portillo-Tarragona et al., 2022 ; Valero-Gil and Scarpellini, 2024
Technological Novelty	TNov	Control Variable	This variable measures the degree to which an invention introduces new and distinctive technological knowledge that departs from existing ideas, methods, or solutions within its domain.	This variable is measured based on the average textual similarity (using both Cosine and Jaccard similarity) of patent to its prior inventions. This average similarity score is then subtracted from 1 to capture the uniqueness of the patent's technological content.	Fontana et al., 2020
Technological Impact	TImp	Control Variable	This variable measures the reach and significance of an invention within the broader knowledge system, reflecting how widely and deeply its underlying technologies are adopted, cited, or built upon by later inventions.	This variable is measured as the time-normalized sum of forward citations across citation generations, with farther generations down-weighted by an attenuation factor.	Higham et al., 2021 ; Corredoira and Banerjee, 2015
Technological Diversity	TDiv	Control Variable	This variable measures the extent to which technology integrates, combines, or connects ideas, methods, or components from multiple technological fields or domains.	This variable is derived from Shannon's Diversity Index, which quantifies the distribution of technological fields within a patent. We calculate the proportion of each IPC/CPC code by dividing the frequency of each code by the total number of IPC/CPC codes assigned to the patent.	Fusillo, 2023 ; De Noni et al., 2018 ; Zhu et al., 2022
Inventor Team size	ITeamSize	Control Variable	This variable measures the total number of inventors in a patent, representing the size of the collaborative team involved in the invention's development.	This variable is the count inventors listed in a patent.	Macher et al., 2024

Note: All variables are aggregated at the patent level – Source: ORBIS IP.

between ITeamSize and INV_StrEmb is slightly higher at 0.546, therefore we performed the Variance Inflation Factor (VIF) diagnostics (see [Appendix A2](#)). These tests are all below the conventional level of 10 ([Kalnins, 2018](#)). Based on the correlation coefficients and the VIF tests, we conclude that multicollinearity is not a significant issue in our model.

3.4.2. Regression analysis

To investigate the determinants of patent-level disruptiveness, we estimate ordinary least squares (OLS) regressions using the reghdfe estimator ([Correia, 2016](#)), which is designed to absorb multiple high-dimensional fixed effects efficiently. Reghdfe employs an iterative algorithm that partials out fixed effects before estimation, enabling the simultaneous inclusion of several dimensions of unobserved

Table 2

Descriptive statistics of the variables.

Variable	Mean	Std. dev.	Min	Max
DI	0.161	0.573	-1	1
INV_KnowBrok	0.0002	0.001	0	0.027
INV_Infl	0.003	0.017	0	0.201
INV_LocCohe	0.408	0.353	0	1
INV_StrEmb	3.325	3.145	0	28
Circular Patent	0.235	0.424	0	1
TNov	0.813	0.103	0.638	1
Timp	32.113	3877.984	0	1,008,794
TDiv	2.002	0.72	0	4,946
ITeamSize	2.834	1.976	1	29

Note: total number of observations = 81,072.

Table 3

Normality tests.

Test	Non-CI	CI
Kolmogorov Smirnov	0.2822***	0.2396***
D'Agostino Statistic	291.99***	539.56***
Anderson-Darling	4310.49***	849.07***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

heterogeneity. This is particularly suited to our context, where both firm-specific heterogeneity and time shocks may confound the relationship between inventor networks, circularity, and disruptiveness.

Our baseline specification takes the disruptiveness index as the dependent variable and includes inventor network characteristics aggregated to the patent level (betweenness, eigenvector centrality, clustering, k-core) as the main predictors. A binary indicator for circular patents and interaction terms between network variables and circularity capture whether network effects differ systematically between circular and non-circular innovations. Additionally, we control technological novelty, impact, and diversity, as well as inventor team size. Standard errors are clustered at the inventor level to address the non-

independence arising from inventors contributing to multiple patents.

$$\begin{aligned}
 \text{Disruptiveness (DI)} = & \alpha + \beta_1 \text{INV_KnowBrok} + \beta_2 \text{INV_Infl} \\
 & + \beta_3 \text{INV_LocCohe} + \beta_4 \text{INV_StrEmb} \\
 & + \beta_5 \text{Circular Patent} + \beta_6 \text{INV_KnowBrok} \\
 & \times \text{Circular Patent} + \beta_7 \text{INV_Infl} \times \text{Circular Patent} \\
 & + \beta_8 \text{INV_LocCohe} \times \text{Circular Patent} \\
 & + \beta_9 \text{INV_StrEmb} \times \text{Circular Patent} + \gamma_1 \text{TDiv} \\
 & + \gamma_2 \text{TNov} + \gamma_3 \text{Timp} + \gamma_4 \text{TeamSize} + \mu_f + \mu_t + \varepsilon_i
 \end{aligned}$$

To ensure robustness, we estimate four complementary specifications: (i) OLS with both firm and year fixed effects using reghdfe, our preferred model that simultaneously absorbs organizational and temporal heterogeneity; (ii) OLS with year fixed effects only; (iii) OLS with firm fixed effects only; and (iv) pooled OLS without fixed effects as a baseline. This sequence allows us to test the stability of our results under progressively weaker controls for unobserved heterogeneity, ensuring that our findings are not artifacts of model choice but reflect robust empirical relationships between inventor networks, circularity, and

Table 4

The disruptiveness of circular and non-circular innovations during the period 2013–2022.

Year	CI Mean	Non-CI Mean	U Statistic	p-Value (CI > Non-CI)	CI > Non-CI?
2013	0.225	0.226	3,410,675.5	0.129	No
2014	0.221	0.199	4,134,663	0.055	Yes
2015	0.231	0.183	5,884,669	3.004E-04	Yes
2016	0.235	0.176	4,600,305.5	8.745E-05	Yes
2017	0.199	0.153	5,195,342.5	0.001	Yes
2018	0.210	0.125	6,072,397.5	5.339E-08	Yes
2019	0.191	0.110	4,466,709	1.180E-07	Yes
2020	0.138	0.091	3,577,775.5	0.001	Yes
2021	0.120	0.108	2,893,908	0.164	Yes
2022	0.128	0.097	1,641,605	0.027	Yes

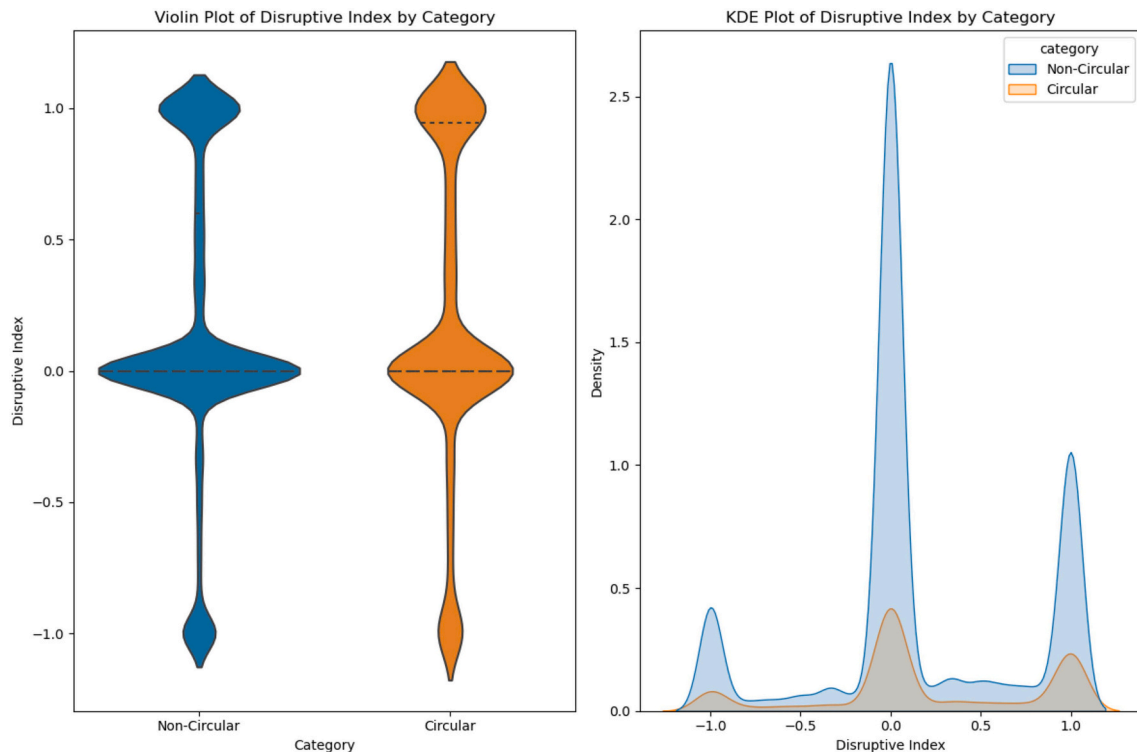
**Fig. 2.** Violin and KDE Plot.

Table 5
Correlation matrix.

Variables	DI	INV_KnowBrok	INV_Infl	INV_LocCohe	INV_StrEmb	Circular Patents	TDiv	TNov	TImp	ITeamSize
DI	1									
INV_KnowBrok	−0.016***	1								
INV_Infl	−0.110***	0.057***	1							
INV_LocCohe	0.017***	−0.039***	−0.061***	1						
INV_StrEmb	−0.072***	0.281***	0.109***	0.357***	1					
Circular Patents	0.028***	−0.006	0.099***	0.103***	0.057**	1				
TDiv	0.026***	0.022***	0.024***	0.068***	0.114***	0.245***	1			
TNov	0.015**	−0.051***	−0.042***	−0.008*	−0.170***	−0.021***	−0.215***	1		
TImp	−0.013**	−0.001	0.0002	0.003	0.002	−0.002	0.002	−0.009	1	
ITeamSize	−0.022***	0.054***	0.024***	0.440***	0.546**	0.049***	0.070***	−0.076***	0.002	1

Table 6
Regression analysis: The effect of inventor network configurations on the disruptiveness of circular innovations.

	OLS with Firm and Year FE	OLS with Year FE	OLS with Firm FE	OLS without FE
	Disruptive Index	Disruptive Index	Disruptive Index	Disruptive Index
INV_KnowBrok	−0.001 (−0.18)	0.001 (0.24)	−0.001 (−0.24)	0.001 (0.21)
INV_Infl	−0.055** (−2.77)	−0.063*** (−3.76)	−0.049* (−2.47)	−0.046** (−2.78)
INV_LocCohe	−0.025** (−3.24)	−0.028*** (−5.49)	−0.029*** (−3.83)	−0.036*** (−7.29)
INV_StrEmb	−0.034*** (−3.51)	−0.034*** (−5.32)	−0.039*** (−3.97)	−0.048*** (−7.77)
Circular Patents	0.046*** (3.32)	0.044*** (4.72)	0.047*** (3.43)	0.042*** (4.52)
Circular Patents # INV_KnowBrok	0.063*** (3.95)	0.086*** (6.07)	0.061*** (3.80)	0.082*** (5.77)
Circular Patents # INV_Infl	−0.035 (−1.75)	−0.032 (−1.95)	−0.040* (−2.04)	−0.049** (−2.94)
Circular Patents # INV_LocCohe	0.312*** (24.19)	0.322*** (34.20)	0.313*** (24.27)	0.324*** (34.39)
Circular # INV_StrEmb	−0.127*** (−8.67)	−0.171*** (−15.12)	−0.124*** (−8.47)	−0.166*** (−14.56)
TDiv	0.010 (1.51)	0.042*** (11.29)	0.002 (0.35)	0.029*** (7.80)
TNov	0.002 (0.45)	0.022*** (5.55)	−0.002 (−0.38)	0.005 (1.40)
TImp	−0.910*** (−8.84)	−0.013** (−2.77)	−0.873*** (−8.45)	−0.012** (−2.75)
ITeamSize	0.008* (2.53)	0.002 (0.97)	0.010** (2.89)	0.007** (2.72)
Constant	−0.087*** (−7.36)	−0.024** (−2.77)	−0.091*** (−7.71)	−0.035*** (−4.18)
No. of Observations	79,788	81,071	79,789	81,072

t statistics in parentheses.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

patent disruptiveness. Moreover, because patents from more recent years may not yet have accumulated sufficient citation depth, which could mechanically compress disruptiveness scores, we perform an additional robustness test by re-estimating the models on the subsample of patents granted up to 2020. This restriction ensures that all focal patents are observed over at least a five-year forward-citation window, consistent with the logic of the Funk and Owen-Smith (2016) disruptiveness measure. The results from this restricted-window sample are substantively unchanged: the direction, statistical significance, and overall pattern of the coefficients remain consistent with those obtained in the full-sample analysis. To conserve space, the corresponding estimates are not reported here, but they are available from the authors upon request.

4. Results

Table 6 presents the results of regressions estimating the relationship between inventor network characteristics, circularity, and patent disruptiveness. Across all four model specifications, firm and year fixed effects, year fixed effects only, firm fixed effects only, and pooled OLS

without fixed effects, the findings are consistent and robust.

Starting with the main effects of network structure, inventor cohesiveness coefficient and embeddedness coefficients are negative and highly significant across all specifications. In the full model with firm and year fixed effects, INV_LocCohe enters at $\beta = -0.0256$ ($p < 0.01$) and INV_StrEmb at $\beta = -0.0349$ ($p < 0.001$), these results provide strong support for H2, indicating that patents developed by teams embedded in tightly knit neighborhoods or in the structural core of the network are systematically less likely to be disruptive. Such positions expose inventors to redundant information flows and conformity pressures, thereby constraining the novel recombination associated with disruption.

Inventor influence (INV_Infl) is also negative and statistically significant across all models ($\beta = -0.0551$, $p < 0.01$ with firm and year fixed effects; $\beta = -0.0631$, $p < 0.001$ with year fixed effects only). This suggests that inventors embedded in influential positions linked to other central actors tend to produce patents that consolidate rather than disrupt established technological trajectories. By contrast, Knowledge Broker (INV_KnowBrok) is consistently insignificant, implying that brokerage roles, while theoretically associated with bridging structural

holes, do not directly translate into disruptive outcomes in this context. Together, these results reinforce the notion that it is not brokerage nor connectivity per se, but rather distance from the structural core and lack of local redundancy that fosters disruptiveness.

Turning to the analysis of the circularity effects, the indicator for circular patents is positive and highly significant across all specifications ($\beta = 0.0464$, $p < 0.001$ in the full model), indicating that circular patents are systematically more disruptive than non-circular patents.

The interaction effects yield strong support for H1a and H2a. The interaction between circularity and inventor structural embeddedness is consistently negative and highly significant ($\beta = -0.127$, $p < 0.001$ in the full model). This means that while patents from inventor teams positioned in a network structural core are generally less disruptive, this tendency is especially pronounced for circular patents. Put differently, disruptive circular innovations are disproportionately likely to emerge from the network periphery, supporting H1a. The interaction between circularity and inventors with a high degree of cohesiveness is strongly positive across all models ($\beta = 0.312$, $p < 0.001$ in the full model; $\beta = 0.324$, $p < 0.001$ in the pooled model). This indicates that while local cohesion usually suppresses disruptiveness, in circular contexts cohesive teams become advantageous, consistent with H2a. Cohesion appears to facilitate the trust and sustained collaboration required to integrate heterogeneous sustainability-oriented knowledge domains.

Additional interactions highlight further nuances. The interaction between circularity and knowledge brokerage is positive and significant ($\beta = 0.0634$, $p < 0.001$), suggesting that brokerage position, while not inherently disruptive, plays a stronger role in enabling disruption in circular contexts where bridging disparate knowledge domains is essential. By contrast, the interaction between circularity and influence is negative and marginally significant in some models ($\beta = -0.0407$, $p < 0.05$ under firm fixed effects), implying that strong alignment with central and influential actors constrains disruptiveness in circular innovations.

The technological control variables show patterns consistent with expectations. Technological diversity is positively associated with disruptiveness in models with year fixed effects ($\beta = 0.0427$, $p < 0.001$), underscoring the role of heterogeneous knowledge integration in enabling systemic departure from established trajectories. Novelty has limited explanatory power, becoming significant only with year fixed effects ($\beta = 0.0228$, $p < 0.001$), suggesting that novelty alone does not guarantee disruption unless it is combined with adoption and future influence. Interestingly, technological impact exhibits a strong negative sign ($\beta = -0.910$, $p < 0.001$ with firm and year fixed effects), supporting the notion that highly cited patents often consolidate rather than disrupt knowledge lineages.

Inventor team size is positive and significant in several models ($\beta = 0.00895$, $p < 0.05$ in the full model), indicating that larger inventor groups contribute to disruptiveness, likely by pooling broader expertise and heterogeneous knowledge domains, although the effect appears weaker than that of structural network variables.

4.1. Additional analysis

Building on our baseline idea that circular innovations are, on average, more disruptive than non-circular ones, we now look specifically at the circular innovation group. As not all circular innovations are disruptive in a knowledge-rerouting sense (De Angelis, 2024), using a network measure of disruptiveness (e.g., Funk and Owen-Smith, 2016), some circular patents would actually reinforce existing knowledge trajectories, because their forward citations continue to co-cite foundational prior art. This is especially likely for energy and material management-related circular patents that demand deep process integration and compliance with exacting standards (Cainelli et al., 2020); such integrative complexity ties new advances to established protocols, making subsequent inventions reference both the focal patent and its predecessors. For example, in GaN LED fabrication, high-current

“droop” is often mitigated through iterative adjustments to epitaxial growth conditions and doping profiles, raising yields and improving energy and material efficiency; these are incremental process refinements rather than novel disruptions (Weinold et al., 2025).

Thus, as an additional step, we re-estimate our regression models on the restricted sample of circular patents only, in order to probe heterogeneity within the circular innovation domain. Specifically, we distinguish between energy-related circular patents (coded as 1) and non-energy circular patents (coded as 0).⁸ This refinement allows us to test whether the network antecedents of disruptiveness differ across circular sub-domains that vary in their technological orientation and knowledge integration demands. This additional analysis enables us to examine whether disruptive circularity is particularly salient for energy-focused and material-focused technologies. In doing so, it extends the contribution of the paper by identifying whether network structures conducive to disruption vary not only between circular and non-circular trajectories but also across distinct circular innovation domains.

The results in Table 7 show that the indicator for energy- and material-related circular patents is negative and significant in the richer specifications ($\beta = -0.0479$, $p < 0.05$), indicating that these circular sub-domains are, on average, less disruptive than other circular patents. Considering the interaction effects, the interaction between energy and material focused circular patents and inventor influence is positive and highly significant ($\beta = 0.0119$; $p < 0.001$), indicating that when these complex circular inventions are developed by inventor teams connected to influential, well-embedded actors, their baseline tendency toward consolidation is offset, i.e., access to central knowledge hubs and top-tier collaborators enables the recombination of heterogeneous capabilities, yielding novel knowledge beyond prior art boundaries. By contrast, interactions with betweenness, clustering, and k-core are small and mostly insignificant, suggesting that within the energy and material-focused circular innovation domain, it is influence or legitimacy at the core, rather than brokerage or local cohesion, that enables circular innovations otherwise oriented toward consolidating or reinforcing existing innovation trajectories to become disruptive.

5. Discussion and conclusion

Our findings provide systematic evidence that circular innovations in the European semiconductor industry are significantly more disruptive than non-circular ones, both in terms of their citation dynamics and in the way inventor networks shape their outcomes. This has important implications for understanding how sustainability-oriented innovations emerge and diffuse within high-tech, resource-intensive sectors. First, the results demonstrate that disruptiveness is closely related to inventors' network configurations, extending prior work that has emphasized novelty, impact, and diversity as drivers of disruptive breakthrough innovations (Fleming and Sorenson, 2001; Fontana et al., 2020). Consistent with earlier studies on disruptive innovation, we find that peripheral positions are critical: patents developed by inventors located outside the structural core are systematically more disruptive, confirming that distance from dominant knowledge flows provides the freedom to experiment with unconventional trajectories (Fleming, 2007; Capponi et al., 2022). This effect is especially pronounced for circular patents, where disruptiveness emerges most strongly from peripheral actors who are less bound by resource-intensive mainstream practices within the semiconductor manufacturing sector. These results reinforce longstanding theories about the role of structural detachment

⁸ We distinguish those circular innovations which are materials and energy-related, and comprise ‘Waste Reduction and Sustainable Production’, ‘Reuse of Energy and Materials’, ‘Resource and Energy Optimization’, and ‘Recovery of Resource and Energy’, and the remaining general circular innovations, which include ‘Repairing and Refurbish’, ‘Refuse Management’, ‘Regenerating and Reactivating’, ‘Repurpose’, and ‘Recycling’.

Table 7

The effect of inventor network configurations on the disruptiveness of subset of circular innovations: energy and material innovations versus other circular innovations.

	OLS with Firm and Year FE	OLS with Year FE	OLS with Firm FE	OLS without FE
	Disruptive Index	Disruptive Index	Disruptive Index	Disruptive Index
INV_KnowBrok	0.054 (1.60)	0.052 (1.86)	0.050 (1.58)	0.037 (1.46)
INV_Infl	−0.096*** (−29.99)	−0.104*** (−49.58)	−0.098*** (−28.29)	−0.106*** (−44.38)
INV_LocCohe	0.326*** (17.23)	0.311*** (18.19)	0.321*** (16.87)	0.304*** (17.69)
INV_StrEmb	−0.129*** (−4.56)	−0.152*** (−6.20)	−0.158*** (−5.66)	−0.180*** (−7.29)
Energy and Material Focused CI (EMCI)	−0.001 (−0.06)	−0.047* (−2.40)	−0.011 (−0.40)	−0.057** (−2.84)
INV_KnowBrok # EMCI	0.001 (0.04)	0.028 (0.90)	−0.0006 (−0.02)	0.035 (1.21)
INV_Infl # EMCI	0.006*** (1.57)	0.011*** (4.51)	0.008 (1.94)	0.014*** (4.96)
INV_LocCohe # EMCI	−0.024 (−1.16)	0.004 (0.24)	−0.027 (−1.28)	0.001 (0.08)
INV_StrEmb # EMCI	0.033 (1.12)	0.006 (0.26)	0.051 (1.74)	0.024 (0.91)
TDiv	−0.0001 (−0.01)	−0.026** (−2.60)	−0.014 (−1.15)	−0.040*** (−4.05)
TNov	0.009 (0.87)	0.057*** (6.65)	−0.002 (−0.22)	0.035*** (4.15)
Timp	−0.871*** (−4.74)	−1.323*** (−8.67)	−0.808*** (−4.33)	−1.252*** (−8.23)
ITeamSize	−0.030*** (−5.27)	−0.037*** (−6.79)	−0.025*** (−4.55)	−0.032*** (−5.99)
Constant	0.110*** (3.76)	0.189*** (8.06)	0.113*** (3.86)	0.190*** (8.09)
No. of Observations	18,364	19,051	18,364	19,051

t statistics in parentheses.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

in enabling novel recombination.

Second, our findings refine the role of inventor cohesion by distinguishing between a general effect and a circularity-specific effect. In line with conventional wisdom, patents developed within tightly clustered inventor groups are generally less disruptive, as local redundancy and conformity pressures limit exposure to novel ideas (Granovetter, 1973; Uzzi and Spiro, 2005). However, this general pattern changes in circularity contexts. In the context of circular innovation, cohesion becomes positively associated with disruptiveness, suggesting that sustained trust-based collaboration among heterogeneous actors facilitates the integration of material science, design, and sustainability expertise. This echoes recent arguments that mission-oriented innovations require deep relational infrastructures to coordinate complex knowledge integration (Innocenti et al., 2021; Mies and Gold, 2021). Taken together, these findings suggest that circular disruption within the semiconductor industry does not stem from isolated mavericks but from cohesive peripheral groups of inventor collectives positioned outside the structural core yet strongly interconnected among themselves. Such configurations resemble what might be termed as disruptive lobbies: coalitions of inventors who, by aligning around shared sustainability missions, create a level of cohesion necessary to challenge incumbent, non-circular technologies while remaining sufficiently detached to escape their constraints.

Third, our findings about technological controls both confirm general patterns in the disruptive innovation literature and reveal a more specific nuance for circular innovation. In both the overall and circular innovation analyses, novelty is positively associated with disruptiveness, although its effects remain contingent and consistently weaker than those of network structure. This supports the view that novelty is a necessary but not sufficient condition for disruption; unless subsequent inventions adopt and build upon it, novel ideas remain isolated (Arthur, 2007). Technological impact likewise shows a consistent negative association across both contexts, suggesting that a focal patent may generate substantial indirect influence as its ideas diffuse through

successors, yet that same diffusion can coincide with the focal being bypassed, implying consolidation rather than displacement (Funk and Owen-Smith, 2016; Yang, 2025). These results reinforce, in general terms, the conceptual distinction between disruption and impact. The main difference arises with technological diversity. While broader technological variety is positively associated with disruptiveness in general, this pattern does not extend to circular innovation, for which the association becomes negative. This indicates that circular innovation disruptiveness is not explained by technological breadth alone. Rather, in this context, the disruptive potential of circular innovation appears to depend more strongly on how heterogeneous knowledge is coordinated through inventor networks than by the breadth of the technological knowledge base alone.

Fourth, while some circular innovations transform existing technological trajectories, others, particularly those focused on energy and material optimization, tend to revitalize rather than displace prior knowledge. In this sense, energy and material-focused circular inventions often act as mechanisms of stabilized renewal, reinforcing incumbent technological lineages by improving their performance, reducing waste, or extending their life cycles. Yet, this apparent continuity conceals a deeper duality. Because energy and material innovations are inherently complex and knowledge-intensive, their development often requires integration across scientific, engineering, and environmental domains. When such innovations are produced through collaborations involving highly central inventors or leading firms, they acquire access to diverse technological capabilities and broader recombination spaces. This interaction between complexity and influence transforms what might otherwise be incremental improvements into highly novel, field-shaping advances capable of displacing existing paradigms. Thus, our study shows that the disruptiveness of circular innovations is emerging not from circularity itself, but from the network configuration through which circular ideas are enacted. Energy and material-focused circular technologies exemplify this contingency as they are typically conservative in structure, yet when embedded

within influential and diverse inventor networks, they can become catalysts of profound technological reorientation.

In conclusion, our study contributes to three ongoing debates. First, it advances research on disruptive circular innovation by demonstrating that circularity-related disruption is distinct from conventional disruption: while peripheral openness remains essential, cohesion can become a resource rather than a liability when innovations are mission-driven. Second, it refines the understanding of circular innovation by showing that circularity is not merely a domain of incremental efficiency improvements, while also making clear that not all circular innovations are inherently disruptive. Instead, their disruptiveness depends on the specific type of circular innovation and on the socio-technical configurations within which they are developed (Blomsma et al., 2022). Third, it contributes to socio-technical transition studies by linking inventor-level networks with systemic outcomes, illustrating how structural peripherality combined with cohesive clustering may serve as the organizational backbone of circular disruption (Geels, 2004; Kuhlmann et al., 2022).

6. Implications and future research

This study contributes to the literature on disruptive innovation in two complementary ways. First, at the level of the general disruptive innovation literature, it confirms and extends the view that disruptive innovation is associated with peripheral openness and structural detachment (Fleming, 2007; Capponi et al., 2022), while highlighting the importance of inventor network structure as a key antecedent of disruptive outcomes in the European semiconductor industry. Second, in relation to the circular innovation literature, it shows that the conditions under which disruption emerges are more specific than in the general case. In mission-oriented domains such as circular innovation, disruption does not arise from peripherality alone; rather, cohesion among peripheral inventors can be enabled by supporting the trust, coordination, and integration of heterogeneous expertise required for circularity-oriented problem-solving. In this sense, our findings refine the conventional association of disruption with loosely connected networks (Burt, 2004; Uzzi and Spiro, 2005) and suggest that, under sustainability pressures, peripheral but cohesive clusters may provide the organizational basis for transformative recombination. By placing disruptiveness within the socio-technical context of the European semiconductor industry, our study clarifies that circular disruption is not merely an application of general disruption theory to a green domain, but a context within which specific collaborative configurations matter more strongly. This also opens promising avenues for future research to examine whether similar network conditions underpin disruptive innovation across other mission-driven domains, such as renewable energy, bio-based materials, or mobility, thereby extending the generalizability of our findings beyond the semiconductor sector.

For managers in the European semiconductor manufacturing sector, the results carry critical implications for innovation strategy and organizational design. Traditional innovation management has emphasized integration into the structural core of industries to maximize visibility, legitimacy, and cumulative advantage. However, our findings suggest that circular innovation disruptiveness is more likely to emerge from collaborations at the periphery, where inventors are less tied to established knowledge regimes and freer to recombine ideas unconventionally. Nevertheless, peripherality alone is not sufficient; cohesion within these groups is essential to sustain the cross-disciplinary collaboration required for circular breakthroughs. For firms, this implies the need to deliberately support boundary-spanning inventor teams that bring together diverse expertise, like device physicists, recycling engineers, and sustainability designers, while ensuring that these collaborations are embedded in cohesive clusters that enable knowledge sharing and trust. Therefore, managers must balance openness and cohesion, encouraging exploratory alliances outside dominant trajectories, while investing in relational structures that make collaboration effective. In practice, this may involve designing dedicated circular innovation units,

cross-sector partnerships, or hybrid consortia that give peripheral actors (startups/SMEs/new labs) both autonomy and relational support. Likewise, resource-dedicated budget for cohesive sub-teams around circular missions could generate novel disruptive ideas that might displace prior trajectories and lead to further development of novel circular innovations. The role of inventor influence in material and energy circular patents also suggests that firms leading in circular transitions are those capable of linking core R&D networks with cross-sectoral sustainability expertise, transforming embeddedness into a source of novelty rather than conformity.

At the policy level, the findings underscore the importance of designing innovation ecosystems that empower peripheral yet cohesive inventor communities as drivers of systemic change. Although recent policy discourse has moved beyond individual firm incentives or aggregate R&D intensity to recognize the role of innovation ecosystems (European Commission, 2022), our results identify an important, nuanced aspect of collaborative research, that is, the structural configuration of collaboration networks matters as much as the technological content of patents. To accelerate the transition to circularity in semiconductor manufacturing, policymakers should therefore focus not only on network-oriented and ecosystem interventions, supporting mission-driven clusters, but also on facilitating cross-sector inventor mobility and incentive collaborations that bridge industrial, disciplinary, and geographic boundaries. Importantly, cohesion within these clusters should not be mistaken for redundancy. Importantly, in circular contexts, cohesive networks enable the trust and sustained engagement required to integrate heterogeneous knowledge domains. EU-level initiatives such as the Green Deal, CE Action Plan, and Chips Act (European Commission, 2019) provide ideal vehicles for embedding these network perspectives into funding and regulatory frameworks, ensuring that circular disruptors are not isolated but instead supported as part of broader collaborative ecosystems.

This study is not without limitations. First, while patents provide rich, standardized indicators of inventive activity, they only capture codified knowledge and may underrepresent non-patented process or business-model innovations that are central to circularity. Future work could triangulate patent-level disruptiveness with firm-level adoption data, sustainability performance indicators, or life-cycle assessments to capture broader transition effects. Second, our comparison between circular and non-circular patents should also be interpreted with caution. As discussed in the classification section, the empirical non-circular category includes patents that are not strictly circular and may therefore contain some environmentally oriented or green inventions that do not meet the specific criteria for circularity. Third, although the improved CD framework mitigates truncation and field-heterogeneity biases, citation-based measures remain sensitive to time windows and sectoral norms; longitudinal replications across other circular-intensive sectors (e.g., batteries, renewable energy, and advanced materials) would test the generalizability of these findings. Fourth, although our models incorporate fixed effects and temporally lagged network measures, some potential endogeneity concerns may remain. Inventor network positions, such as centrality or peripherality, as well as the orientation toward circular innovation, may be jointly shaped by unobserved factors, such as organizational strategy, technological opportunity, managerial selection, or prior collaborative capabilities, which we were not able to measure and include in our study. Accordingly, our findings should be interpreted as associative rather than strictly causal. Finally, network measures are aggregated to the patent level, abstracting from intra-organizational dynamics and the role of non-inventor actors such as suppliers or customers. Future studies could enrich this socio-technical lens by incorporating multiplex networks that map interactions across technological, organizational, and policy layers. Future research could also strengthen identification by using propensity score matching, instrumental-variable approaches, or natural experiments that exploit exogenous variation in collaboration opportunities or policy shocks.

CRediT authorship contribution statement

Priyanshu Protim Pathak: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Silvia Massini:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Lucia Piscitello:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

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.

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Appendix A

The input dataset consisted of 81,072 patent records (2013–2022) with assigned circular (1) or non-circular (0) labels derived from IPC–CPC combinations aligned with CE principles. Each patent's title and abstract were preprocessed to remove HTML artifacts and language placeholders. We used “anferico/bert-for-patents,” a domain-specific transformer pre-trained on patent text and fine-tuned it in a five-fold cross-validation scheme for three epochs per fold under a balanced binary setup. Model performance was evaluated using Precision, Recall, F1, and AUC. We then compared model-based predictions (bert_pred) with our rule-based labels (rule_label), flagging cases of disagreement or low-confidence agreement for manual inspection.

Table A1
Performance metrics of the BERT model verification against IPC–CPC rule-based classification.

Metric	Value
Total patents	81,072
Agreement (%)	92.85
Disagreement (%)	7.15
True Positives (rule = 1, pred = 1)	16,759
True Negatives (rule = 0, pred = 0)	58,521
False Positives (rule = 0, pred = 1)	3850
False Negatives (rule = 1, pred = 0)	2542
Precision	
Mean	0.813
Standard Deviation	0.004
Recall	
Mean	0.868
Standard Deviation	0.012
F1 Score	
Mean	0.839
Standard Deviation	0.004
ROC-AUC	
Mean	0.947
Standard Deviation	0.001

The BERT model verification shows strong alignment with the IPC–CPC rule-based classification (Agreement = 92.85%, Precision = 0.813, Recall = 0.868, F1 = 0.839, ROC–AUC = 0.947), indicating high semantic consistency between patent text and our circularity taxonomy. Disagreements (7.15%) primarily arose from two sources: (i) false negatives, where genuinely circular patents were classified under closely related IPC/CPC subclasses that fall outside the strict boundaries of our predefined circular taxonomy; and (ii) false positives, where patents contained broad sustainability or efficiency-oriented language without a clear linkage to circular design or closed-loop material flows. We manually reviewed and updated the dataset for very-high-confidence false positives and the false negatives ($p \geq 0.90$) and used the patterns observed to refine the classification strategy. Overall, the verification strengthens reliability.

Table A2
VIF Table.

Variables	VIF	1/VIF
INV_StrEmb	1.69	0.59186
ITeamSize	1.59	0.62815
INV_LocCohe	1.32	0.75793
TDiv	1.12	0.89069
INV_KnowBrok	1.12	0.89269
Circular Patents	1.09	0.92093
TNov	1.08	0.92678
INV_Infl	1.04	0.96517
TImp	1.01	0.99009
Mean	1.23	

Table A3
Model Section for optimal Alpha Value⁹.

Model	Alpha	MSE	R2	Coefficient
M1	0.01	0.011111	0.050543	0.0243
M2	0.06	0.011109	0.050743	0.0243
M3	0.11	0.011098	0.051444	0.0245
M4	0.16	0.011098	0.051441	0.0245
M5	0.21	0.011095	0.051697	0.0245
M6	0.27	0.011106	0.050815	0.0243
M7	0.32	0.011116	0.049943	0.0241
M8	0.37	0.011128	0.048922	0.0239
M9	0.42	0.011141	0.047826	0.0236
M10	0.47	0.011154	0.046707	0.0233
M11	0.53	0.011167	0.045598	0.0231
M12	0.58	0.011179	0.044523	0.0221
M13	0.63	0.011191	0.043494	0.0225
M14	0.68	0.011203	0.042519	0.0223
M15	0.73	0.011211	0.041601	0.0221
M16	0.79	0.011224	0.040739	0.0218
M17	0.84	0.011233	0.039934	0.0216
M18	0.89	0.011242	0.039181	0.0214
M19	0.94	0.011252	0.038479	0.0212
M20	1	0.011255	0.037823	0.0211

⁹ The alpha that demonstrated the highest R2 and a relatively low MSE, while maintaining a high coefficient, was considered optimal

Data availability

Data will be made available on request.

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